Enhancing the Accuracy of Photofluorescent Uranium Ore Sorting under Dust and Noise Using Swin Transformer and Image Restoration Techniques

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Abstract

The photofluorescent uranium ore sorting method based on deep learning can effectively separate ore and waste, but its imaging is easily affected by environmental factors such as dust and noise, resulting in image degradation and reduced sorting accuracy. Therefore, in this paper, a dust image acquisition system was designed to obtain a test set of synthetic ore images with different dust concentrations, which was used to explore the influence of dust on uranium ore sorting. Five common noises, including Gaussian noise, Rayleigh noise, Gamma noise, uniform noise and salt-and-pepper noise, were used to synthesize ore test sets in different proportions to explore the influence of noise on sorting accuracy. The above dust and noise test sets were input into the Swin Transformer model to obtain the accuracy respectively, and the evaluation indicators such as confusion matrix and Grad-CAM algorithm were used for intuitive analysis, and finally, the MIRNet-v2 module was introduced. The results showed that when the dust concentration reached 10 g/m^3, the accuracy increased from 89.94% to 93.24%. When the noise ratio reaches 0.3, the accuracy of the module for Gamma noise and salt-and-pepper noise was increased from 75% and 77.13% to 85.67% and 87.78%, respectively, which has a better removal effect than Gaussian noise, Rayleigh noise and uniform noise. The research in this paper will provide new ideas for the engineering application of photofluorescent uranium ore sorting methods and solve the influence of complex environmental factors for improving uranium ore sorting.

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Enhancing the Accuracy of Photofluorescent Uranium Ore Sorting under Dust and Noise Using Swin Transformer and Image Restoration Techniques

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Abstract

Deep learning-based photofluorescent uranium ore sorting methods can effectively separate ore from waste, but their performance is easily compromised by environmental factors such as dust and noise, leading to image degradation and reduced sorting accuracy. This paper addresses these challenges through several contributions. First, we designed a dust image acquisition system to generate a test set of synthetic ore images under varying dust concentrations, enabling systematic investigation of dust effects on uranium ore sorting. Second, we synthesized ore test sets contaminated with five common noise types—Gaussian, Rayleigh, Gamma, Uniform, and Salt-and-pepper noise—at different proportions to explore their impact on sorting accuracy. Third, we evaluated these contaminated test sets using a Swin Transformer model, employing evaluation metrics including confusion matrices and the Grad-CAM algorithm for intuitive analysis. Finally, we introduced the MIRNet-v2 module for image restoration. Experimental results demonstrate that at a dust concentration of 10 g/m^3, the accuracy improved from 89.94% to 93.24%. When the noise ratio reached 0.3, the module increased accuracy for Gamma noise and Salt-and-pepper noise from 75% and 77.13% to 85.67% and 87.78%, respectively, showing superior removal performance compared to Gaussian, Rayleigh, and Uniform noise. This research provides new insights for the engineering application of photofluorescent uranium ore sorting methods and offers solutions to mitigate the influence of complex environmental factors.

Keywords: Uranium ore sorting; Deep learning; Ore dust; Different noises

INTRODUCTION

China's uranium resources are widely distributed but characterized by relatively low average grades and high mining costs [?]. Hard rock uranium ore is typically extracted through open-pit blasting, which generates substantial radioactive dust and mixes ore with waste rock, resulting in high uranium leaching costs and low resource recovery rates [?]. Consequently, developing advanced ore sorting technology and equipment is particularly critical. The success of intelligent sorting technologies fundamentally depends on the accuracy of ore identification and the capability of information processing algorithms [?, ?].

Previous research has explored various sensor-based sorting approaches. Li et al. proposed applying X-ray fluorescence (XRF) for bulk ore classification using receiver operating characteristics (ROC) [?]. Robben et al. introduced X-ray transmission (XRT) for ore classification, demonstrating its application at the San Rafael tin mine [?]. Ore sorting represents an important solution to ore loss and dilution, yet China' s lagging uranium beneficiation technology and equipment have become a bottleneck restricting the development of uranium mining and metallurgy. Building on this context, we previously proposed a photofluorescent uranium ore sorting method based on deep learning [?]. This method leverages the photofluorescence properties of uranium: when irradiated by ultraviolet light (365 nm), uranium minerals excite and emit green fluorescence (492–577 nm), enabling photoluminescence-based sorting.

Mechanical processes such as crushing, sorting, and transportation constitute the primary sources of mine dust, which forms air pollution in mining areas and adversely impacts both operators and equipment. Zhang proposed a machine learning-based method for uranium energy spectrum logging and inversion, primarily employing BP neural networks, SVM, and random forest for quantitative uranium interpretation [?]. Demonstrating the trend toward more advanced models, Cao et al. combined prompt gamma neutron activation analysis (PGNAA) with a Vision Transformer (ViT) model, achieving exceptionally high precision in copper ore grade identification and outperforming traditional deep learning models [?].

In 2021, researchers explored moisture effects on various ore particles, developing deep learning-based RGB image classification models capable of classifying coal particles across two density levels (<1.8 & >1.8 g/cm^3) under varying water gradients [?]. Liu et al. addressed insufficient data in image sensor-based ore sorting by investigating suitable small deep learning models for ore image classification, considering model depth, structure, and dataset size [?]. However, when capturing photoluminescent ore images with high-definition cameras, the images are often affected by various interferences and noise during generation and transmission, adversely impacting subsequent image processing and visual effects. Therefore, photoluminescence-based uranium ore separation methods combined with deep learning algorithms must account for the influence of ore dust and different noise types in the separation environment.

Recent domestic research has extensively investigated open-pit mineral dust mechanisms, migration patterns, concentration prediction, monitoring and early warning, and prevention and control technologies. Huang reviewed dust prevention and control development in Chinese coal mines, summarizing various technologies categorized by application stage and environment into dust suppression, open-pit dust removal, and mine dust collectors [?]. To guide mines in selecting appropriate dust prevention measures, Zhou clarified primary dust generation processes and hazard status through field investigation, analyzing open-pit quarry dust prevention and control technologies according to dust reduction approaches [?]. Luan proposed a machine learning-based solution for accurate dust concentration estimation using random forest methods with Markov chain correction, employing wind speed, temperature, humidity, and atmospheric pressure as inputs to estimate PM2.5, PM10, and TSP outputs [?]. To analyze sulfide ore powder concentration distribution during loading, transportation, and unloading, Li used FLUENT software to simulate migration and dispersion processes with dust generation rate, wind speed, and dust source location as variables [?]. Furthermore, Jiang et al. investigated water and dust adhesion effects on hyperspectral imaging for iron ore classification, proposing a new spectral differential feature combined with a random forest classifier to effectively mitigate these influences [?].

Additionally, when using high-definition cameras to capture photoluminescent ore images, objective factors such as transmission technology bottlenecks or environmental conditions during image acquisition inevitably cause quality issues including blurriness and distortion, necessitating preprocessing with image denoising as a critical component. To address visibility degradation from dust, Cao et al. proposed a three-stream color balance and transmittance fusion method for dehazing coal mine dust images, which often exhibit a unique black shift not handled by conventional methods [?]. For sand dust images, Si et al. developed a fusion-based strategy combining an improved Gaussian model for color correction with a CNN for dust removal to enhance visibility [?]. From a traditional signal processing perspective, Yanqin presented a multi-level denoising method for mine monitoring images combining spatial domain filters with wavelet transforms to tackle mixed noise [?]. More recently, deep learning approaches have demonstrated dominant performance. Hu designed a lightweight CNN with heterogeneous kernels (HKCNN) for efficient noise removal [?]. To balance performance and computational cost, Wang et al. introduced an efficient lightweight network using progressive residual learning and convolutional attention fusion [?]. Zhang proposed a group sparsity residual constraint model with weighted logarithm penalty (GSRC-log) for image restoration, adaptively adjusting penalty intensity to preserve fine details [?]. Fan proposed a blurred image feature-guided CNN (BFCNN) with a novel blur adjustment strategy that converts the one-way denoising process into a two-way process for more accurate results [?]. Tian proposed a cross-transformer denoising CNN (CTNet) with serial, parallel, and residual blocks to obtain clear images of complex scenes [?]. Du proposed a flexible image denoising network (CFMNet) by equipping a U-Net backbone with multi-layer conditional feature modulation [?]. Additionally, segmentation model advantages are worth adopting, as demonstrated by Fang et al.' s BAF-Net, a bidirectional attention fusion network integrating CNNs and transformers for pepper leaf segmentation [?]. In 2023, Liu et al. proposed GCHA-Net, a global context and hybrid attention network for automatic liver segmentation [?].

In previous work, we proposed a photofluorescent uranium ore sorting method

[?]. Based on this research background and identified limitations, we conducted environmental impact studies on our previous Swin Transformer-based sorting model. Focusing on mineral dust effects on uranium ore separation, we designed a dust image acquisition system and processed images through extraction, background removal, and pasting to obtain synthetic ore test sets with different dust concentrations. To investigate noise effects, we input five ore test sets contaminated with different proportions of Gaussian, Rayleigh, Gamma, Uniform, and Salt-and-pepper noise into the Swin Transformer model, using confusion matrices and Grad-CAM algorithms for intuitive analysis, and finally introduced the MIRNet-v2 module to ensure model accuracy within acceptable ranges.

II. MODEL BUILDING AND EXPERIMENTATION

A. Holistic Process Framework

In previous work, our team established a study on photofluorescent uranium ore sorting based on deep learning. As shown in Fig. 1 [Figure 1: see original paper], using hard rock uranium ore as the experimental object and leveraging the photofluorescence properties of uranium minerals, we proposed a separation method based on photoluminescence. Uranium ore was stimulated by ultraviolet irradiation to release green fluorescence, and we established a uranium ore dataset divided into training, validation, and test sets at a 7:2:1 ratio. We then combined deep learning with CNN and Transformer models to improve uranium ore image classification accuracy and classification rates. Channel visualization diagrams, confusion matrices, and Grad-CAM diagrams were used to demonstrate the model' s operation process in photofluorescent uranium ore image sorting and analyze characteristics affecting classification weights. Finally, we proposed an optimization study addressing mineral dust and different noise influences, with the overall process framework shown in Fig. 2 [Figure 2: see original paper].

B. Dust Image Acquisition

1. Dust Image Acquisition Device Mechanical processes such as crushing, sorting, and transportation are the main sources of mine dust, which refers to solid particles suspended in the air. In dust control technology, solids with particle sizes of 1-200 μm or even larger particles that can float in air are considered dust [?]. In the design and operation of photoluminescent uranium ore sorting devices, dust characteristics are closely related to model classification accuracy. Fully utilizing dust properties or implementing appropriate measures to modify unfavorable conditions for separation accuracy can significantly improve dust purification effects and ensure normal operation of photoluminescent uranium ore sorting equipment.

Particle size is an important parameter characterizing the state of ore dust particles, representing the most direct external manifestation of particle size and shape. Additionally, particle size is a crucial physical property of ore dust, with many related properties depending on it.

Dust density: There are certain voids between ore dust particles, and some ore dust contains many internal voids.

Adhesion: The adhesion of ore dust refers to the tendency of ore dust particles to adhere to other surfaces (such as water) or to themselves. Since dust generated in beneficiation production is smaller, it exhibits greater water absorption capacity and stronger adhesion. Consequently, after ore crushing, the ore is washed before entering the conveyor.

To realize dust image acquisition, we designed the overall acquisition scheme shown in Fig. 3 [Figure 3: see original paper]. The acquisition system consists of an optical device, an image device, and a dust concentration adjustment device. The image device comprises image acquisition and image post-processing equipment, while the dust concentration adjustment device primarily acts on the dust to be measured. Currently, the main approach for collecting dust images involves capturing dust concentration in a fixed enclosed space using a high-definition camera.

The collection process was as follows: A 40 cm × 25 cm × 20 cm rectangular glass box was constructed with glass plates as the dust image collection chamber. The dust to be measured was weighed on a high-precision mass scale to obtain a known quantity. The light source was activated before dust flowed through the image acquisition and processing device, allowing dust to flow steadily in the photosensitive area. Light scattered after irradiating dust particles, and image data in the light-sensitive area was collected by the high-definition camera. Dust mass was continuously changed through the dust concentration adjustment device, altering dust concentration in the fixed space. Repeated acquisition established the correspondence between dust concentration and image.

Overall structure: The core design of the acquisition device comprises the optical system and image acquisition device. Dust images are significantly affected by light source, optical path, scattering angle, and other factors, making optical system design fundamental to ensuring stable acquisition. The optical structure design is shown in Fig. 4 [Figure 4: see original paper], using a known-volume 40 cm × 25 cm × 20 cm rectangular glass box as the dust image collection chamber. Dust enters the box from one side, while incident light irradiates dust particles from the top of the glass box, making the dust entry direction perpendicular to the incident light. To collect dust images across the entire section, multiple LEDs were placed evenly above the glass box to ensure uniform illumination and reduce image acquisition errors caused by uneven background light.

2. Dust Image Processing Process Various dust image processing algorithms exist. The main purpose of this paper is to obtain images of different dust concentrations and synthesize them onto the test set portion of the same dataset. The overall processing process is shown in Fig. 5 [Figure 5: see original paper]. First, dust particles are extracted from dust images. Then, the background is removed from the images after dust particle extraction. Finally, dust particles in RGBA format with different concentrations are pasted and synthesized onto the test set to obtain the "contaminated" photofluorescent uranium ore data test set.

Dust image: At the dust image collection site in the rectangular glass box (40 cm × 25 cm × 20 cm), a high-precision electronic balance was used to add experimental dust in concentration gradients through the dust concentration adjustment device: 10 mg, 20 mg, 30 mg, 40 mg, 50 mg, 100 mg, 150 mg, 200 mg, 250 mg, 300 mg, 350 mg, and 400 mg (Fig. 3 [Figure 3: see original paper]).

Dust particle extraction: OpenCV was used to filter the background by color (HSV). The H value of the experimental dust (gray) was approximately 13–30, the S value approximately 13–162, and the V value approximately 40–116.

Background removal: Background removal was implemented using the Python Pillow (PIL) library to traverse each pixel in the image, introducing alpha channel transparency. True color graphics of the RGB color model contain three color information channels (red, green, blue), each using 8-bit color depth for a total of 24 bits containing all color information. To achieve transparency effects, another 8 bits of information was attached for processing and storage. The color of pixels on the black background of the dust particle extraction image was changed to transparent, obtaining the RGBA image format divided into images after background removal.

Dust paste synthetic ore image: The dust image sub-images and photofluorescent uranium ore dataset with removed background were processed by adding the Python Pillow (PIL) library to obtain image length and width information, resize sub-images, and finally paste them into the uranium ore test set to obtain dust-synthesized ore images.

C. Different Noise Images Added

Image noise is an important factor that interferes with and hinders human cognition and understanding of image information. Images are often degraded due to various noise interferences during generation and transmission, adversely affecting subsequent image processing and visual effects. Noise types can be categorized from different perspectives. The distribution and magnitude of noise in images are irregular—that is, random—with general correlation between noise and images. Based on noise probability distribution types, classification primarily includes Gaussian noise, Rayleigh noise, Gamma noise, Uniform noise, and Salt-and-pepper noise. The probability density functions of some common image noises are analyzed separately \cite{30–32}.

1. Gaussian Noise Although every pixel in an image may be altered when polluted with Gaussian noise, each pixel changes to a different grayscale value, and the "contaminated" grayscale values still contain useful information. The probability density function of Gaussian noise follows a Gaussian distribution (also known as a normal distribution), shown in Eqs.(1):

$$P(z) = e^{-(z-\mu)^2}$$

Where z is the noise level, μ is the mean of the noise level, σ is the standard deviation of the noise level, and σ^2 is the variance. When z follows a Gaussian distribution, approximately 70% of values fall within the $(\mu - \sigma, \mu + \sigma)$ interval and about 95% fall within the $(\mu - 2\sigma, \mu + 2\sigma)$ interval.

2. Rayleigh Noise The probability density function describing the statistical characteristics of Rayleigh noise is shown in Eqs.(2):

$$P(z) = \begin{cases} b(z-a)e^{-(z-a)^2} & z \geq a \\ 0 & z < a \end{cases}$$

The mean μ is calculated according to Eqs.(3) and the variance σ^2 according to Eqs.(4):

$$\mu = a + \sqrt{\frac{b(4-\pi)}{2}}$$

3. Gamma Noise The probability density function describing the statistical properties of Gamma noise is shown in Eqs.(5):

$$P(z) = \begin{cases} \frac{a^b z^{b-1}}{(b-1)!} e^{-az} & z \geq 0 \\ 0 & z < 0 \end{cases}$$

where $a > 0$ and b is a positive integer. The mean μ and variance σ^2 are calculated according to Eqs.(6) and Eqs.(7), respectively.

4. Uniform Noise The probability density function describing the statistical properties of Uniform noise is shown in Eqs.(8):

$$P(z) = \begin{cases} \frac{1}{b-a} & a \leq z \leq b \\ 0 & \text{otherwise} \end{cases}$$

where $a > 0$ and b is a positive integer. The mean μ and variance σ^2 are calculated according to Eqs.(9) and Eqs.(10), respectively:

$$\mu = \frac{a+b}{2}$$

5. Salt and Pepper Noise The probability density function is shown in Eqs.(11):

$$P(z) = \begin{cases} P_a & z = a \\ P_b & z = b \\ 0 & \text{otherwise} \end{cases}$$

where P_a and P_b are both > 0. For 8-bit grayscale images, $a, b = 0$ or 255, with the larger value displayed as white dots and the smaller value as black dots. Because this noise is distributed across the image somewhat like pepper and salt particles, it is called Salt-and-pepper noise.

Based on 1,187 ore fluorescence images irradiated with ultraviolet light on 4-10 cm particle size ore, expanded by data enhancement algorithms using batch flip/rotation operations in ACDSee, the existing collected ultraviolet irradiation ore fluorescence images were rotated by 180° and 90° respectively in batches, expanding the image data to 3,561 images to create Dataset 1. Dataset 1 has a 7:2:1 ratio for training, validation, and test sets. Five different types of noise "pollution" were added to the test set images. For the Gaussian distribution, the mean and variance are parameters required to generate the distribution, with adjusted (mean, var) values of (0.05, 0.05), (0.1, 0.1), (0.2, 0.2), and (0.3, 0.3) added to the original ore images. For the Rayleigh distribution, variance is the parameter required to generate the distribution, adjusted to 0.05, 0.1, 0.2, and 0.3 and added to the original ore images. For the Gamma distribution, variance is the parameter required to generate the distribution, adjusted to 0.05, 0.1, 0.2, and 0.3 and added to the original ore images. For the Uniform distribution, the upper bound (high) and lower bound (low) of the random number are parameters required to generate the distribution, adjusted to (0.05, 0.05), (0.1, 0.1), (0.2, 0.2), and (0.3, 0.3) and added to the original ore images. The Salt-and-pepper noise ratio (prob) is a parameter required to generate Salt-and-pepper noise, adjusted to 0.05, 0.1, 0.2, and 0.3 and added to the original ore images.

III. RESULTS AND DISCUSSION

Experimental analysis was performed by inputting ore test sets with different dust concentrations and different proportional noise into the Swin Transformer model. The experimental structure was intuitively analyzed through evaluation indices including confusion matrix, precision, recall, specificity, and F1-Score.

Through the image processing process (Fig. 5 [Figure 5: see original paper]), the image acquisition and processing device obtained dust images at concentrations of 0.5 g/m^3, 1 g/m^3, 1.5 g/m^3, 2 g/m^3, and 2.5 g/m^3 as low-concentration echelons; 5 g/m^3, 7.5 g/m^3, and 10 g/m^3 as medium-concentration echelons; and 12.5 g/m^3, 15 g/m^3, 17.5 g/m^3, and 20 g/m^3 as high-concentration echelons (Fig. 6 Figure 6: see original paper). Fig. 6(b) shows extracted dust particles at different concentrations. Fig. 6(c) displays split images after background removal. Fig. 6(d) shows the final dust-synthesized ore images. To further explore the effectiveness of the Swin Transformer model for uranium ore sorting in mineral dust environments, synthetic ore test sets with different dust concentrations were input into the Swin Transformer model to obtain accuracy metrics, which were compared with the original dataset test set to determine the impact of different dust concentrations on model classification.

When the three dust concentration gradient segments (low, medium, and high) were added, the model classification accuracy gradually decreased with increasing dust concentration, as shown in Fig. 8 [Figure 8: see original paper]. Specifically, at low concentrations of 0–2.5 g/m^3, classification accuracy decreased by no more than 0.61% with increasing concentration, maintaining 93.29% accuracy at 2.5 g/m^3—only a 1.53% overall decrease from the dust-free accuracy of 94.82%. At medium concentrations of 5–10 g/m^3, classification accuracy decreased by more than 1.52% with increasing concentration, dropping to 89.94% at 10 g/m^3—a 4.88% decrease compared to the dust-free classification accuracy of 94.82%. At high concentrations of 12.5–20 g/m^3, classification accuracy decreased by more than 1.61% with increasing concentration, falling to 84.67% at 20 g/m^3—a 10.15% overall decrease from the dust-free accuracy of 94.82%.

IV. ANALYSIS OF EXPERIMENTAL RESULTS

Confusion matrix: To clearly observe classification accuracy comparisons across different datasets in the same model, this study introduced the confusion matrix as a visual tool and the most obvious method [?, ?]. The test confusion matrix based on the Swin Transformer model at dust concentrations of 0.5–20 g/m^3 was analyzed for each test set, as shown in Fig. 7 [Figure 7: see original paper].

Precision, recall, and F1 scoring metrics were introduced to validate the generated model. **Precision** is defined by Eqs.(12):

$$\text{Precision} = \frac{TP}{TP + FP}$$

where true positive (TP) indicates waste rock correctly classified as waste rock, and false positive (FP) indicates uranium ore incorrectly classified as waste rock.

Recall is the proportion of correctly predicted waste rock among all actual waste rock results, defined by Eqs.(13):

$$\text{Recall} = \frac{TP}{TP + FN}$$

where false negative (FN) indicates waste rock misclassified as uranium ore.

Specificity is the proportion of correctly predicted uranium ore among all actual uranium ore results, defined by Eqs.(14):

$$\text{Specificity} = \frac{TN}{TN + FP}$$

where true negative (TN) indicates uranium ore correctly classified as uranium ore.

F1-Score combines precision and recall results, with values ranging from 0 to 1, where 1 represents the best model output. The F1-Score metric is defined by Eqs.(15):

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Table S1 shows the model evaluation indices for the 0.5–20 g/m^3 dust concentration test set.

Grad-CAM algorithm: To observe the distribution of classification weights in input images and analyze ore surface areas with higher classification weights, this study introduced the Grad-CAM algorithm [**?**]. The Grad-CAM algorithm calculates model classification weights and overlays them as a heat map proportionally onto the input image (Eqs.(16)):

$$\text{Grad-CAM} = \text{ReLU}\left(\sum_k \alpha_k^c A_k\right)$$

where Z is the width $\times$ height of the feature layer, y_c is the score predicted by the network for the category, A_k^{ij} is the data at location (i, j) in the k-th feature layer, and α_k^c is the weight of the k-th feature layer.

In this study, two types of ore images (<100 ppm and >100 ppm) were selected to analyze classification weight and ore surface area distribution in the Swin Transformer model' s Grad-CAM, as shown in Fig. 9 [Figure 9: see original paper]. In Grad-CAM diagrams, classification weights are displayed through a JET color gradient bar, with dark blue areas representing low classification weights and dark red areas representing high classification weights. As classification weight increases, colors transition from dark blue (low weight) through green to dark red (high weight). Through the confusion matrix combined with the Grad-CAM algorithm, it is evident that as concentration increases, the red area on the ore surface affecting classification weight gradually expands, causing the model to gradually lose classification accuracy.

A. Effect of Different Noise Types on Uranium Ore Sorting

As shown in Fig. 10 [Figure 10: see original paper], test sets of ore images synthesized with five noise types were input into the Swin Transformer model to obtain accuracy metrics, which were compared with the original dataset test set to determine the impact of different noise types on model classification. Confusion matrices are shown in Fig. 11 [Figure 11: see original paper] to further evaluate model classification performance across different proportional noise test sets. Corresponding quantitative metrics (accuracy, precision, recall, and F1-score) under five different proportional noise test sets are summarized.

The Grad-CAM algorithm was employed to enhance model interpretability, as shown in Fig. 12 [Figure 12: see original paper]. Through the confusion matrix combined with Grad-CAM analysis, model classification accuracy gradually decreases with increasing noise ratio. Among these, in the test set Grad-CAM with added Gamma noise, the proportion of red areas affecting classification weight was the smallest. However, according to model evaluation descriptions, in image test sets after Gamma noise addition, the model significantly reduced weight for correct classification, primarily using incorrect regions as the basis for correct classification weight. In contrast, in test set Grad-CAM with Salt-and-pepper noise, the proportion of red areas affecting classification weight was the largest, indicating that the model faced difficulty in making classification decisions, resulting in greater resource consumption during classification.

B. Optimized Research

In view of dust effects, we introduced the MIRNet-v2 module [?], with the schematic diagram shown in Fig. 13 [Figure 13: see original paper]. At its core is the multi-scale residual block, containing several key elements: (a) parallel multi-resolution convolutional streams extracting semantically rich (fine-to-coarse) and spatially accurate (coarse-to-fine) representations, (b) information exchange for capturing contextual information, (c) non-local attention mechanisms with aggregated features from different streams, and (d) residual context blocks for attention-based feature extraction.

After the module removes dust from test datasets with different concentrations, the cleaned test set images are input into the Swin Transformer to obtain test accuracy. Comparing this with unprocessed images yields Fig. 14 [Figure 14: see original paper], which shows the specific accuracy and improvement of model classification on test datasets before and after processing, where improvement % = Post-processing classification accuracy % - Pre-processing classification accuracy %. According to Fig. 14 [Figure 14: see original paper], in the low-concentration echelon range of 0.5–2.5 g/m^3, the accuracy of the pre-processing test dataset does not decrease significantly, indicating good model robustness in this range. Consequently, the accuracy improvement for model classification on processed test datasets does not exceed 1%. In the medium-concentration echelon range of 5–10 g/m^3, the accuracy of the pre-processing test dataset for model classification decreases gradually. After introducing the MIRNet-v2 module, the accuracy of the processed test dataset for model classification gradually increases by up to 3.3%. In the high-concentration echelon range of 12.5–20 g/m^3, the accuracy of model classification decreases most significantly in the pre-processing test dataset, dropping by 10.14% when concentration reaches 20 g/m^3. After MIRNet-v2 module processing, accuracy increases by 3.74%, indicating that model classification accuracy needs further improvement in the high-concentration echelon, and the introduced MIRNet-v2 module requires further optimization.

In view of the influence of five noise types, the MIRNet-v2 module was also introduced. The module performed noise removal on test datasets with different types and proportions, and the cleaned test set images were input into the Swin Transformer to obtain test accuracy. Comparing this with test accuracy from different types and proportions yields Fig. 15 [Figure 15: see original paper] and Fig. 16 [Figure 16: see original paper], which show the accuracy of different proportional noise classification for different types.

Under different Gaussian noise ratios, the accuracy of the processed model classification increased from 80.49% to 88.71% after MIRNet-v2 module noise removal with 0.3 Gaussian noise added. Under different Rayleigh noise ratios, introducing the MIRNet-v2 module with 0.3 Rayleigh noise added increased processed model classification accuracy from 81.40% to 88.41%. Under different Gamma noise ratios, introducing the MIRNet-v2 module with 0.3 Gamma noise added increased processed model classification accuracy from 75.00% to 85.67%. Under different Uniform noise ratios, introducing the MIRNet-v2 module with Uniform noise ratio of 0.6 added increased processed model classification accuracy from 82.32% to 90.24%. Under different Salt-and-pepper noise ratios, introducing the MIRNet-v2 module with 0.3 Salt-and-pepper noise ratio added increased processed model classification accuracy from 77.13% to 87.78%. The Swin Transformer model was established for Uniform noise, where classification model accuracy decreases the least with increasing noise ratio. For Gamma noise, classification model accuracy decreases the most with increasing noise ratio. After introducing the MIRNet-v2 module, the accuracy of the processed test set increased by 10.67% and 10.65% respectively after adding 0.3 ratio noise to Gamma noise and Salt-and-pepper noise, indicating that the introduced MIRNet-v2 module has good noise removal effects on Gamma noise and Salt-and-pepper noise.

V. CONCLUSION

In view of mineral dust influence on uranium ore separation, we designed a dust image acquisition process. Through image processing, test sets of synthetic ore images with different dust concentrations were input into the Swin Transformer model trained in previous work. Test set accuracy gradually decreased with increasing dust concentration, dropping to 84.67% when dust concentration reached 20 g/m^3. Evaluation indices including confusion matrix and Grad-CAM algorithm were used for intuitive analysis, and finally an optimization study was proposed for dust influence. Results show that the introduced MIRNet-v2 module maintained accuracy at 94.12% in the low-concentration dust range of 0–2.5 g/m^3 and at 93.24% in the medium-concentration dust range of 5–10 g/m^3, effectively removing dust and guaranteeing model testing accuracy within certain ranges.

Regarding noise influence on uranium ore separation, we introduced five different noise types and noise addition methods. After adding five different noise types with various proportions to the test set, test set accuracy gradually decreased with increasing noise ratio. Evaluation indices including confusion matrix and Grad-CAM algorithm were used for intuitive analysis. The Swin Transformer model was aimed at Uniform noise, where classification model accuracy decreases the least with increasing noise ratio. When noise ratio reaches 0.3, the module accuracy for Gamma noise and Salt-and-pepper noise increased from 75% to 85.67% and from 77.13% to 87.78%, respectively, demonstrating the best removal effect compared to Gaussian noise, Rayleigh noise, and Uniform noise.

VI. CONTRIBUTIONS STATEMENT

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Yan Zhang, Jun Qiu, Chun-Qing Fu, Tao Ou, Qi Liu, Ren-Bo Wang, and Bin Tang. Yan Zhang and Jun Qiu wrote the first draft of the manuscript, and all authors commented on previous versions. All authors read and approved the final manuscript.

VII. CONFLICT OF INTEREST

The authors declare that they have no competing interests.

VIII. DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Science Data Bank at: 31253.11.sciencedb.29390

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Note: Figure translations are in progress. See original paper for figures.