Received 14 December 2022, accepted 1 January 2023, date of publication 4 January 2023, date of current version 8 March 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3234075

APPLIED RESEARCH

Intelligent Deployment Solution for Tabling Adapting Deep Learning

YOU KESHUN[1] AND LIU HUIZHONG[1,2]

[1]Department of Mechanical and Electrical Engineering, Jiangxi University of Science and Technology, Ganzhou 341000, China

[2]Jiangxi Mining and Metallurgical Mechanical and Electrical Engineering Technology Research Center, Ganzhou 341000, China

Corresponding author: Liu Huizhong (huizhong6@163.com)

This work was supported in part by the Jiangxi Province Key Research and Development under Project 20212BBE53026.

ABSTRACT This article presents an intelligent deployment solution for tabling that utilizes deep learning techniques. The solution involves adapting deep learning semantic segmentation algorithms with DeepLab V3+ to extract multi-dimensional image features, enabling the mapping of relationships between mineral ore belt characteristics and operating parameters using a multi-output support vector regression model optimized using a sparrow search algorithm (ssa-msvr). The proposed solution integrates image recognition software and data processing method, which significantly improves the efficiency and effectiveness of mineral processing, providing a promising avenue for further research and development in this field.

INDEX TERMS Mineral processing, deep learning semantic segmentation, multi-dimensional image features, support vector regression model.

I. INTRODUCTION

To perceive the operating state of the tabling, the traditional operation controls of the tabling are up to the operator to sense the mineral ore belt of the tabling and understand the characteristic information such as the shape and color of the ore belt. Control parameters such as horizontal flushing water, bed slope, stroke, and stroke rate are adjusted accordingly to complete. Since the difference of everyone's experience, technical proficiency, and sense of responsibility, there are unavoidable errors and uncertainties in determining whether the operating state of the tabling is normal, if only by observing the mineral ore belt of the tabling with the naked eye. Therefore an objective, high-precision and fast method is urgently required to obtain the characteristic parameters of the mineral ore belt and to quickly and accurately determine the real-time operating status and indicators of the tabling.

Nowadays, the overwhelming majority of researchers attempted to optimize the operating parameters of the tabling and predict indicators using artificial neural networks (ANN) based on industrial data [1], [2]. However, these studies achieved low accuracy and reliability in the optimization process. In recent years, with the development of machine vision technology, it has been widely applied in various fields [3], [4], [5], [6], including feature extraction of mineral ore belt images [7]. The gray-scale calculus image processing algorithm is utilized to calculate the boundary points of the ore belt, obtain the characteristics of the boundary line, and ultimately determine the width and color characteristics of the ore belt, enabling complete segmentation of the mineral ore belt [8]. Building on this research, the Beijing General Research Institute of Mining and Metallurgy (BGRMM) has developed an automatic mining system for gravity beneficiation tabling [9], which is mainly composed of a mining device and an inspection robot with a camera and image processing software, which improves the efficiency of mineral separation by the tabling, instead of workers intercepting concentrates, and realizing automatic interception of concentrates on the gravity beneficiation tabling [10], [11]. These studies start from the method of mineral ore belt image processing to achieve the optimization of mineral interception operations, opening new directions for later optimization studies and

The associate editor coordinating the review of this manuscript and approving it for publication was Mohammad Shorif Uddin.

intelligent deployment. And then multi-threshold color image segmentation algorithm based on krill optimization, and multi-threshold color image segmentation algorithm based on improved firefly algorithm, etc. which are applied to the image segmentation of the mineral ore belt [12], [13]. Increasingly effective deep convolutional neural network models and image processing algorithms are applied to the process of mineral identification and separating [15], However, all researchers currently use deep learning only to obtain the boundary separation points of the ore zone, ignoring the characteristics of the line and surface of the mineral ore belt, and all the feature detection algorithms based on deep learning serve to replace the manual realization of accurate concentrate interception, only to achieve the optimization of the interception operation, ignoring the optimization of multiple operating parameters, such as the optimization of the performance of the equipment itself of stroke and stroke times, so it is difficult to achieve the intelligent deployment.

To obtain multi-scale effective geometric features compared with other image recognition algorithms, which specifically includes all extractable features of points, lines, and surface from the entire mineral zone area. A semantic segmentation algorithm based on the excellent performance of DeepLab V3+ series is suitably applied to the detection of such rich features, which is of great significance for constructing the ML model of relationship between image features and parameters of the horizontal flushing water, slope angle, stroke, and stroke rate and other operating parameters, as well as the beneficiation indicators of the recovery rate and concentrate grade [16], Because rich and multi-scale image features can provide maximum dimensionality for the input of ML models, thus effectively guaranteeing the accuracy of relationship model mapping [8]. Traditional ML models have some shortcomings in accuracy and most of them are only suitable for single-output prediction. In this study, a multi-output support vector regression model optimized by a sparrow search algorithm (SSA-MSVR) is used to construct a mapping model between the image features of the mineral ore belt and the attributes of the tabling equipment, whose biggest advantage is that the SSA is used to optimize two important hyperparameters of the SVR to obtain the maximum prediction accuracy of the MSVR. Finally, combined with advanced deep learning and data mining technologies, and friendly optimization strategies, we have realized the intelligent deployment solution of the mineral processing of tabling.

II. MULTI-SCALE FEATURE EXTRACTION OF MINERAL ORE BELT IMAGE THROUGH DEEP LEARNING

In this study, feature extraction of mineral ore belt images is the core element to achieve the goal of intelligent mineral processing. In order to deploy the research results to practical applications as soon as possible, we need to consider many application issues, such as, whether the algorithm is stable and reliable enough, whether the software is mature, whether the communication is feasible, etc.

A. ACQUISITION AND PRODUCTION OF DATASETS

In order to generate high-quality datasets with composite model characteristics, we preprocessed the raw images generated from industrial, mainly through methods of denoising and image enhancement [17]. In this study, the image enhancement method of gray-scale transformation and the denoising method of Gaussian filtering is mainly used. During image preprocessing, we performed uniform scaling of the image, the image gray value was normalized to a reasonable gray value range, and through the reasonable allocation of pixel value weights, a large number of image preprocessing parameter combinations are obtained, which will be applied to the training of deep learning segmentation models.

B. TRAINING AND INFERENCE EVALUATION OF DEEP LEARNING MODEL

The advanced deep learning semantic segmentation with DeepLab v3+ continues to improve on the architecture of the DeepLab v3 by introducing Encoder-Decoder, which is commonly used for semantic segmentation, in order to fuse multi-scale information. As shown in **FIGURE 1** the resolution of the features extracted by the encoder can be arbitrarily controlled, and the accuracy and time consumption are balanced by null convolution. Two pre-trained deep learning neural network models are provided, namely, dl_segmentation_enhanced and dl_segmentation_compact with DeeLab V3+. The result of semantic segmentation is an output image where the pixel values represent the specified category of corresponding pixels in the input image, for general deep learning (DL) networks, deeper feature mappings representing more complex features are often smaller than the input images. To obtain an output of the same size as the input, it uses a split network consisting of two components: an encoder and a decoder. The encoder has determining the characteristics of the input image, and since the information is "encoded" in a compressed format, the decoder needs to reconstruct the information into the desired result, in which case each pixel is assigned to a class, but when classifying the pixels, overlapping instances of the same class are not distinguished as distinct. Edge extraction is a special case of semantic segmentation, in which the trained model is designed to distinguish between two categories: "edge" and "background."

As shown in **FIGURE 2**, independent of the deep learning method used, the data has to be provided to the model following certain conventions. The model receives a dictionary for each input image, such a dictionary contains images and, in the case of training and evaluation, also contains information such as basic fact annotations, and as output, the model returns a dictionary with the results. Although the model itself is not required, dictionaries are used during training and evaluation.

As shown in ***Table 1***, the training of the model is done on a personal notebook, using a professional indus-

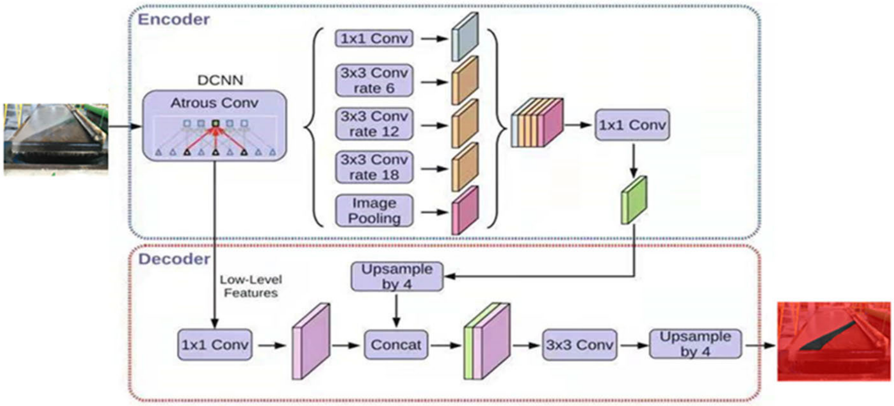


FIGURE 1. Semantic segmentation model in HALCON.

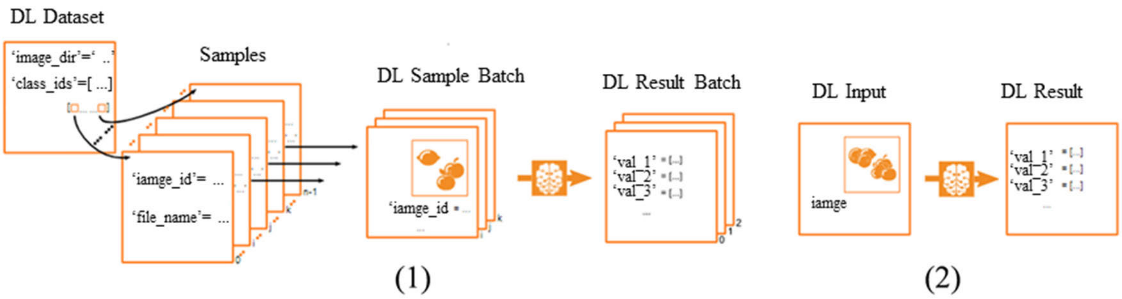


FIGURE 2. Schematic illustration of the dictionaries serving as model input: (1) Training and evaluation (2) Inference.

trial camera and data acquisition software for datasets acquisition, and a server environment with running ability of deep learning is built. In order to facilitate the later model deployment and the intelligent application of mineral separation process, HALCON is used as our development script.

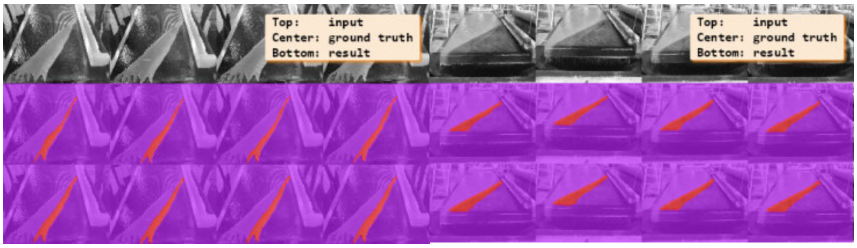
At present, the most commonly-used evaluation index in semantic segmentation is the mIOU. The mIOU is a standard evaluation index for image segmentation work, which calculates the overlap ratio of the intersection of two sets and their union. It calculates the difference between the real segmentation and the segmentation predicted by models, the per-class intersection over union (IOU) gives for a specific class the ratio of correctly predicted pixels to the union of annotated and predicted pixels. In image semantic segmentation of DL, many criteria are usually used to evaluate the accuracy of the model's inferred results. In addition to IOU and its variants, pixel accuracy and its variants also are included. Pixel Accuracy (PA) is the simplest measure, which is the percentage of pixels that are correctly labeled. Mean Pixel Accuracy (MPA) is a simple improvement of PA, which calculates the proportion of correctly classified pixels in each class, and then calculates the average of all classes.

As shown in ***Table 2***, the training parameters of the DL model are set uniformly, and the final training results of the model are visualized in **FIGURE 3**. It can be seen from **FIGURE 3** that the datasets with two scenarios have very

TABLE 1. Software and hardware.

Laboratory equipment	GT62VR 7RE
Data acquisition equipment	Pylon viewer，Basler acA5472-5gc GigE
Device memory	256gSSD,1T
Memory of GPU	GTX1070, 8g
Running memory	16g
Programming environment	HALCON20.11,
Operating environment	DeepLearn Tool,

similar segmentation effects in the DL semantic segmentation model. The training effects of the two DL semantic segmentation models on datasets I and datasets II are excellent, and there is no over-fitting or unqualified *mIOU* value. From the statistical results in ***Table 3*** and ***Table 4***, in the results of datasets I, dl_segmentation_enhanced is slightly more time-consuming, but the *mIOU* value during training is higher than dl_segmentation_compact. And for the datasets II, dl_segmentation_enhanced has a slight advantage in time consumption, but the *mIOU* value is lower than dl_segmentation_compact by more than 10%, which is enough to show that scene images similar to datasets II are more suitable for the deep semantic segmentation model using dl_segmentation_compact.



(1) Datasets I (2) Datasets II

FIGURE 3. Training results of datasets.

TABLE 2. Setting of training parameters.

Epoch	*Interation*	*Loss*	*Learning_rate*	*Batch_size*	*momentum*	*Weight_prior*
20.0	700	0.0892	0.000100	2	0.990000	0.000050

TABLE 3. Training of datasets I.

	Loss	*Time elapsed*	*mIOU on validation set*	*mIOU on training set*
dl_segmentation_compact	00759	1m 31s	0.868	0.889
dl_segmentation_enhanced	0.0892	1m 57s	0.882	0.896

TABLE 4. Training of datasets II.

	Loss	*Time elapsed*	*mIOU on validation set*	*mIOU on training set*
dl_segmentation_compact	0.0780	1m 58s	0.903	~
dl_segmentation_enhanced	0.0791	1m 31s	0.805	~

Thus, we compared two sets of different styles of image datasets from the mineral ore belt, combined with the two deep learning semantic segmentation models, and we conducted four sets of experiments. From the overall experimental effect, in the training process, since dl_segmentation_enhanced has a more complex neural network structure than dl_segmentation_compact, the loss value is always more. For application scenarios similar to the image features of Datasets I, the enhanced dl_segmentation_ is recommended as the model to deployment and practical application, and for application scenarios similar to the image features of Datasets II, the dl_segmentation_compact is recommended as the model to deployment and practical application.

III. INTELLIGENT DEPLOYMENT SOLUTION

Modeling is an important and integral part of optimization [21], the adaptive adjustment method for multi-operating parameters combines the results of the MV, ML, automatic control technologies and it is an optimization algorithm proposed through the exploration of big data modelling, and the deep learning image processing algorithm as a whole, which is an important foundation for the intelligent control of the beneficiation process, and an effective idea to realize the monitoring and intelligent process of tabling beneficiation. ML with optimization methods have been widely and maturely applied in mining equipment [22]. With the help of these mature research results and applications, this study also designs a more reasonable optimization method by the corresponding applications [23].

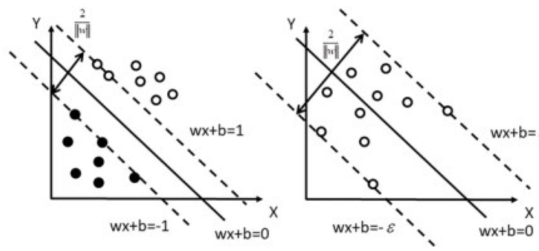


FIGURE 4. SVM and SVR.

A. RELATIONSHIP MAPPING BETWEEN MINERAL ORE BELT AND ATTRIBUTES OF THE TABLING EQUIPMENT

To more realistically map the relationship between image of ore belt and the attributes of tabling, in addition to the need for rich image features as input, the prediction accuracy and of the model should be considered. Traditional ML is difficult to achieve high accuracy with multiple inputs and multiple outputs [24], so this paper proposes a ML learning method based on SSA-MSVR.

As shown in **FIGURE 4**, the goal of SVM is to maximize the "distance" to the nearest sample point in the hyperplane, while the goal of SVR is to minimize the "distance" to the

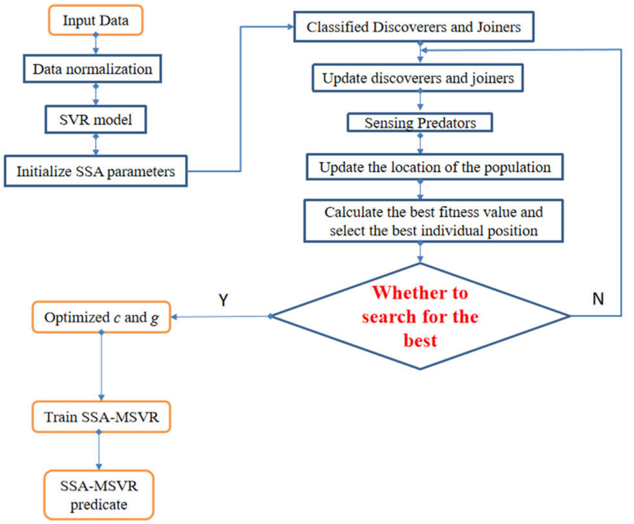


FIGURE 5. SSA-MSVR.

farthest sample point in the hyperplane, and the larger the interval in SVR, the more low-performance it is. SVR is one of the excellent, accurate and robust regression algorithms, insensitive to dimensionality, can handle linearly separable and linearly indistinguishable data, has high stability, fast algorithm updates, and generally chooses RBF as the kernel function [25]. There are two key optimization parameters affecting the SVR model, one is the penalty coefficient (c) and the other is the kernel coefficient (g), the larger the value of c, the greater the penalty and the worse the error tolerance, its influence on the range of Gaussian action corresponding to each support vector, and the larger the g, the worse the generalization performance.

As shown in **FIGURE 5**, the sparrow search algorithm (SSA) first divides the population into discoverers and joiners in the process of finding the optimal SVR hyperparameters. Suppose a population is set up as a matrix X.

$$X = \begin{bmatrix} X_{11} & X_{12} & \ldots & X_{1d} \\ X_{21} & X_{22} & \ldots & X_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n1} & X_{n2} & \ldots & X_{nd} \end{bmatrix} \tag{1}$$

where X_{ij} is the position of the i-th sparrow in the j-th dimension, n is the population size, and d is the dimensionality of the objective function variable space. The discoverer provides directions to capture food for the entire population, so it has a larger search range and the location iterations are updated as follows.

$$X^{t+1} = \begin{cases} X^t * e^{\left(-i/_{\alpha T}\right)} & If\ \ Safe \\ X^t + Q & If\ \ Unsafe \end{cases} \tag{2}$$

where t is the current number of iterations, T is the set maximum number of iterations, X_t and X_{t+1} are the positions of the sparrow before and after the iteration, and Q is the normal random number. When the discoverer is aware of the

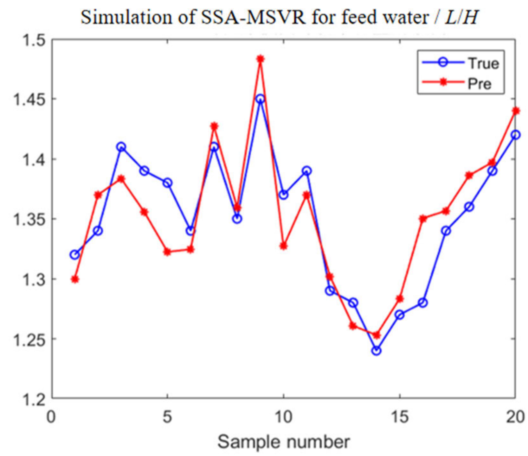


FIGURE 6. Simulation of system for feed water flow.

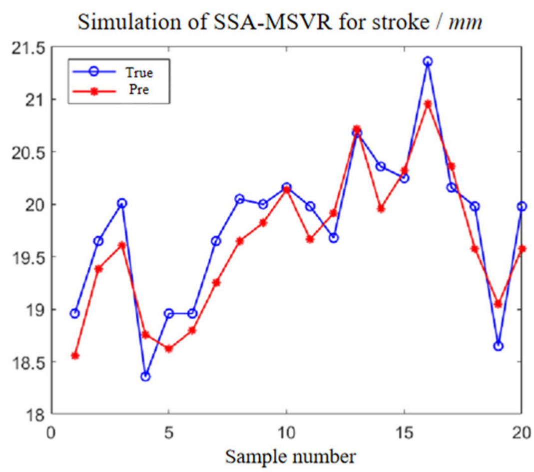


FIGURE 7. Simulation of system for stroke.

danger, it warns the population, which optimizes its position in order to find a safe area.

$$X^{t+1} = \begin{cases} Q * e^{\left(X_L - X^t/_{i^2}\right)} & If\ \ Lower\ fitness \\ X_p^{t+1} + \left|X^t - X_p^{t+1}\right| * L * A^+ & Others \end{cases} \tag{3}$$

X_P^t is the optimal position of the discoverer, X_L is the global worst position, L is a matrix with all elements 1, and A is a random matrix with 1 or -1. $A^+ = A^T(AA^T)$.

The stability of the mapping relationship determines the effect of the system on the monitoring of the mineral ore belt and processing status of the tabling, which in turn affects the accuracy of the adjustment requirements of the system's parameters, and ultimately affects the system's optimization results for processing indicators and operating parameters. Thus the analysis of the ML model in the system is of great significance for the simulation results of operating parameters and processing indicators.

TABLE 5. Simulation results of the ML model for the operating parameters and processing indicators of the tabling.

	MSE	*RMSE*	*MAE*	*R^2*
Feed water flow	0.00132	0.02458	0.028654	0.85895
Stroke	0.10175	0.34527	0.30241	0.90654
Stroke rate	0.24561	0.35642	0.25634	0.99574
Slope angle	0.01015	0.06547	0.040241	0.89857
Concentrate grade/%	0.16524	0.38695	0.378652	0.99658
Recovery rate/%	0.12457	0.39885	0.385654	0.98675

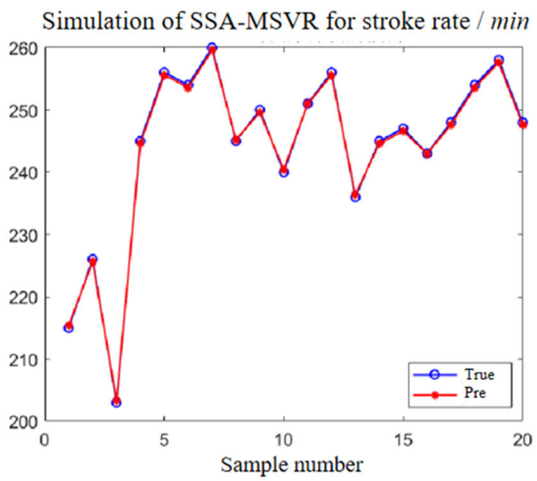


FIGURE 8. Simulation of system for stroke rate.

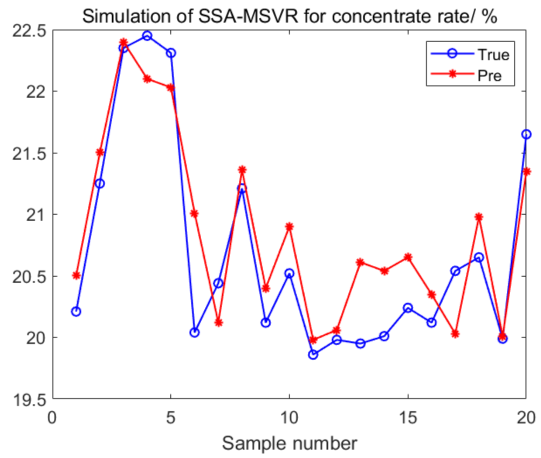


FIGURE 10. Simulation of system for concentrate grade.

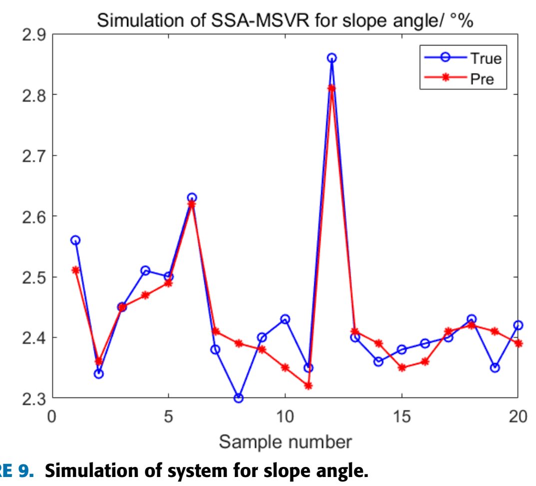


FIGURE 9. Simulation of system for slope angle.

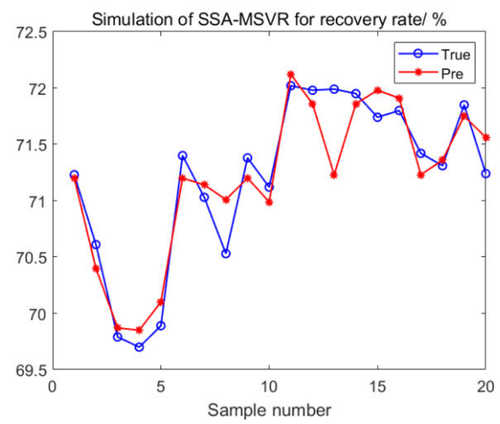


FIGURE 11. Simulation of system for recovery rate.

As shown in **FIGURE 6** to **FIGURE 11**, which are the simulation results of the system for the four operating parameters of the tabling, feed water flow, stroke, stroke rate, slope angle, and the concentrate grade and recovery rate. The 20 groups of data from actual operating parameters and processing indicators of concentrators and the data predicted by the system simulation are obtained and are compared to calculate the accuracy and error of the simulation. As shown in ***Table 5***, the simulation accuracy of the model is analyzed from the Mean Square Error (*MSE*), Mean Absolute Error (*MAE*), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (*MAPE*) and coefficient of R^2, respectively, which are used to evaluate the performance of ML models for regression predictions, and the smaller the *MSE* and *RMSE*, the better the fitting effect of the model, the higher the R^2, the more realistic the model, when the R^2 is greater than 0.8, the model has a very high authenticity. The smaller the *MAPE*, *MAE* and *MAPE* are, the better accuracy of the model. It can be seen that the larger the simulated value, the larger the simulated error value, but the better the fitting effect, and The higher the *MAPE*, such as the value of stroke rate, recovery rate, stroke and concentration rate, which indicates that the ML model in the system has a good ability to learn

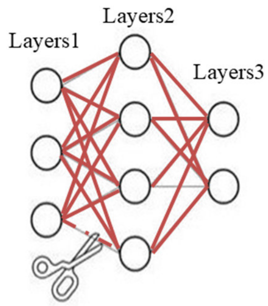


FIGURE 12. Lightweighting methods of the model.

the of the larger values. But on the whole, the ML model in the system has very high accuracy to meet the industrial demand when predicting the operating parameters and processing indicators, and it has extremely high authenticity and reliability.

IV. LIGHTWEIGHTING DEPLOYMENT

In view of the complex working principle and large computational power consumption of deep learning models, lightweight deployment of deep learning models is required in practical applications. In deep learning models with mainly neural network connections, shearing becomes one of the most efficient and simple lightweighting methods.

As shown in **FIGURE 12**, the general idea of pruning is to cut off the unimportant connections between neurons and set the unimportant parameters in the weight matrix to zero, combined with a sparse matrix for storage and computation [26]. In order to ensure the performance of the model itself, it is necessary to iteratively prune one small step at a time, and the specific practice is to sort the weight parameters according to their numerical size, and to set the last $k\%$ of the size ranking to zero, where $k\%$ is the compression rate.

A. IMAGE PROCESSING SYSTEM

To realize intelligent deployment solution of the tabling, independently developed software plays a crucial role. An image recognition system of mineral ore belt feature for the beneficiation process is developed in this study. The entire function of this system is developed in the VS programming environment, combined with inference module of HALCON's deep learning model. As shown in **FIGURE 13**, before the image recognition software on the desktop is opened, the backend server and PLC control system need to be started first. After the software is opened, the communication with the server and the PLC can be automatically realized, and the upper right corner of the software will display that the system works normally and the PLC connection is successful. From the effect of recognition, the mineral ore belt in the process of beneficiation is correctly identified, the characteristics of the strip are transmitted to the server in real-time, and the server sends out the requirements of

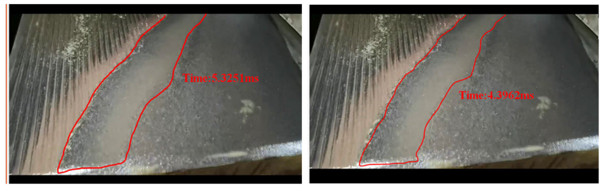


FIGURE 13. Image recognition system (the first image is the previous feature recognition effect of mineral ore belt image, and the second is the under the tabling operation parameters have been optimally tuned).

adjusting the operating parameters such as feed water flow, slope angle, stroke, and stroke rate, to the PLC according to the multi-parameter adaptive adjustment method, after the operating parameters are adjusted, the geometric characteristics of the mineral ore belt are constantly fluctuating. Since the trained model is compressed by parameter pruning and sharing when it is embedded in the system, only a few milliseconds are occupied in the recognition of mineral ore belt.

V. CONCLUSION

This paper presents a novel intelligent deployment solution for tabling in mineral processing using deep learning semantic segmentation algorithms with DeepLab V3+. The authors obtained two sets of image datasets from a real concentrator with different mineral ore belt characteristics and evaluated the algorithm's extraction effectiveness using evaluation indicators of *mIOU* and *PA* of image segmentation. They proposed a mapping relationship model between the characteristics of the mineral ore belt and operating parameters using SSA-MSVR and achieved considerable performance in fitting effect and prediction accuracy for the intelligent beneficiation system. The authors also developed a real-time monitoring software for mineral processing using lightweight deployment of pruning. The research results demonstrate that this intelligent deployment solution greatly improves the intelligence of the tabling and lays a solid foundation for the intelligent realization of the beneficiation plant.

ACKNOWLEDGMENT

The authors sincerely appreciates the data and technical support provided by related companies and researchers and especially thanks to his supervisor for all kinds of help and Jiangxi Provincial Department of Science and Technology and Jiangxi Provincial support of key research and development projects.

COMPLIANCE WITH ETHICAL STANDARDS

Ethical approval and Informed Consent: Written informed consent for the publication of this article has been obtained from Jiangxi University of Science and Technology and all authors.

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 article.

REFERENCES

[1] R. J. Manser, R. W. Barley, and B. A. Wills, "The shaking table concentrator—The influence of operating conditions and table parameters on mineral separation—The development of a mathematical model for normal operating conditions," *Minerals Eng.*, vol. 4, nos. 3–4, pp. 369–381, 1991, doi: 10.1016/0892-6875(91)90142-I.

[2] L. Panda and S. K. Tripathy, "Performance prediction of gravity concentrator by using artificial neural network—A case study," *Int. J. Mining Sci. Technol.*, vol. 24, no. 4, pp. 461–465, Jul. 2014, doi: 10.1016/j.ijmst.2014.05.007.

[3] N. Banus, I. Boada, A. Bardera, and P. Toldrà, "A deep-learning based solution to automatically control closure and seal of pizza packages," *IEEE Access*, vol. 9, pp. 167267–167281, 2021, doi: 10.1109/ACCESS.2021.3135973.

[4] D. Wang, X.-S. Yang, D.-J. Liu, and T.-H. Wang, "Method of detecting wear of rigid tank way of vertical shaft based on machine vision," *Proc. SPIE*, vol. 12127, Dec. 2021, Art. no. 121270B.

[5] B. Huang, J. Liu, M. Chen, and Q. Fan, "Recognition of blurring alphabet character on timing pulley drawing based on HALCON image processing technology," *J. Phys., Conf. Ser.*, vol. 2074, no. 1, Nov. 2021, Art. no. 012015.

[6] L. Kai, M. Minghan, L. Yuehui, and H. Weiqiang, "Cob angle recognition algorithm based on machine vision," in *Proc. Int. Conf. Mach. Learn. Intell. Syst. Eng. (MLISE)*, Jul. 2021, pp. 357–361.

[7] W. Liguan, C. Sijia, J. Mingtao, and T. Siyu, "Beneficiation method of wolframite image recognition based on Deep learning," *Chin. J. Nonferrous Met.*, vol. 30, no. 5, pp. 1192–1201, 2020.

[8] H. Liu and K. You, "Research on image multi-feature extraction of ore belt and real-time monitoring of the tabling by semantic segmentation of DeepLab V3+," in *Advances in Artificial Intelligence and Security* (Communications in Computer and Information Science), vol. 1586, X. Sun, X. Zhang, Z. Xia, and E. Bertino, Eds. Cham, Switzerland: Springer, 2022, doi: 10.1007/978-3-031-06767-9_3.

[9] K. You and H. Liu, "Research on optimization of control parameters of gravity shaking table," *Sci. Rep.*, vol. 13, p. 1133, 2023, doi: 10.1038/s41598-023-28171-5.

[10] W.-W. Yang et al., "Development and application of intelligent inspection robot for mineral processing shaker," *Non-Ferrous Met., Mineral Process.*, no. 5, pp. 102–106, 2020.

[11] Y. Keshun and L. Huizhong, "Research on model construction and control parameters optimization of the separation process of the tabling," Jiangxi Univ. Sci. Technol., Ganzhou, China, Tech. Rep., 2022, doi: 10.27176/d.cnki.gnfyc.2022.000557.

[12] L. He and S. Huang, "An efficient krill herd algorithm for color image multilevel thresholding segmentation problem," *Appl. Soft Comput.*, vol. 89, Apr. 2020, Art. no. 106063.

[13] L. He and S. Huang, "Modified firefly algorithm based multilevel thresholding for color image segmentation," *Neurocomputing*, vol. 240, pp. 152–174, May 2017.

[14] L. Chiqin, "Design of an automatic ore access system based on vision," Kunming Univ. Sci. Technol., Kunming, China, Tech. Rep., 2020.

[15] M. Zheng, Z. Lei, and K. Zhang, "Intelligent detection of building cracks based on deep learning," *Image Vis. Comput.*, vol. 103, Nov. 2020, Art. no. 103987, doi: 10.1016/j.imavis.2020.103987.

[16] Z. Chen, J. Yang, L. Chen, and H. Jiao, "Garbage classification system based on improved shufflenet v2," *Resour., Conservation Recycling*, vol. 178, p. 106090, 2022, doi: 10.1016/j.resconrec.2021.106090.

[17] R. Barth, J. IJsselmuiden, J. Hemming, and E. J. V. Henten, "Data synthesis methods for semantic segmentation in agriculture: A *Capsicum annuum* dataset," *Comput. Electron. Agricult.*, vol. 144, pp. 284–296, Jan. 2018, doi: 10.1016/j.compag.2017.12.001.

[18] T. Huang, B. Zheng, J. Zhang, C. Yi, Y. Jiang, Q. Shui, and H. Jian, "Mango surface defect detection based on HALCON," in *Proc. IEEE 5th Adv. Inf. Technol., Electron. Autom. Control Conf. (IAEAC)*, Mar. 2021, pp. 2627–2631.

[19] Y. Zou and T. Chen, "Laser vision seam tracking system based on image processing and continuous convolution operator tracker," *Opt. Lasers Eng.*, vol. 105, pp. 141–149, Jun. 2018, doi: 10.1016/j.optlaseng.2018.01.008.

[20] S. Masubuchi, E. Watanabe, Y. Seo, S. Okazaki, T. Sasagawa, K. Watanabe, T. Taniguchi, and T. Machida, "Deep-learning-based image segmentation integrated with optical microscopy for automatically searching for two-dimensional materials," *NPJ 2D Mater. Appl.*, vol. 4, no. 1, pp. 1–9, Mar. 2020.

[21] C.-N. Wang, F.-C. Yang, V. T. T. Nguyen, Q. M. Nguyen, N. T. Huynh, and T. T. Huynh, "Optimal design for compliant mechanism flexure hinges: Bridge-type," *Micromachines*, vol. 12, no. 11, p. 1304, Oct. 2021.

[22] H. Liu and K. You, "Optimization of dewatering process of concentrate pressure filtering by support vector regression," *Sci. Rep.*, vol. 12, May 2022, Art. no. 7135, doi: 10.1038/s41598-022-11259-9.

[23] N. T. Huynh, T. V. T. Nguyen, and Q. M. Nguyen, "Optimum design for the magnification mechanisms employing fuzzy logic–ANFIS," *Comput., Mater. Continua*, vol. 73, no. 3, pp. 5961–5983, 2022.

[24] K. You, G. Qiu, and Y. Gu, "Rolling bearing fault diagnosis using hybrid neural network with principal component analysis," *Sensors*, vol. 22, no. 22, p. 8906, Nov. 2022.

[25] X. Wang and Y. Zhong, "Statistical learning theory and state of the art in SVM," in *Proc. 2nd IEEE Int. Conf. Cogn. Inform.* IEEE, 2003.

[26] X. Jiang, N. Wang, J. Xin, X. Xia, X. Yang, and X. Gao, "Learning lightweight super-resolution networks with weight pruning," *Neural Netw.*, vol. 144, pp. 21–32, Dec. 2021.

YOU KESHUN was born in Le'an, Fuzhou, Jiangxi, China, in 1997. He received the academic master's degree in mechanical engineering from the Jiangxi University of Science and Technology, in June 2022, where he is currently pursuing the Ph.D. degree in metallurgical engineering.

He has four computer software copyrights and national invention patents during his postgraduate study. He has presided over one provincial and ministerial level fund project and published three SCI and EI papers, such as Optimization of Dewatering Process of Concentrate Pressure Filtering by Support Vector Regression, Research on Image Multi-feature Extraction of Ore Belt and Real-Time Monitoring of the Tabling by Sema ntic Segmentation of DeepLab V3+, and Multi-Feature Extraction of Mineral Ore Belt of Tabling Through Deep Semantic. His research interests include the optimization control of metallurgical processes and the development of intelligent equipment.

LIU HUIZHONG was born in Xinfeng, Jiangxi, China, in 1969. He is currently a Professor and the Doctoral Supervisor with the School of Mechanical and Electrical Engineering, Jiangxi University of Technology, and the Director of Jiangxi Mining and Metallurgy Mechanical and Electrical Engineering Technology Research Centre. He has been engaged in the research and development of high-efficiency mineral processing equipment, mineral processing process simulation and control technology for more than thirty years. He has presided over the development of "BL series spiral chute," "BPF series automatic high efficiency filter press," "flotation machine level control system," "BXF cyclone particle size analyzer" and other products and technologies. His research achievements have won one National Science and Technology Progress Second Class Award, one Hubei Science and Technology Progress First Class Award, one Beijing Science and Technology Progress Second Class Award, and three China Nonferrous Metals Industry Science and Technology Progress Second Class Awards. At present, he is mainly engaged in teaching and research on high-efficiency mineral processing equipment, process simulation of mineral processing and mineral processing intelligence.