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Hierarchical Intelligent Control Method for Mineral Particle Size Based on Machine Learning

Guobin Zou [1,2,3,*], Junwu Zhou [1,2], Tao Song [2,3], Jiawei Yang [2,3] and Kang Li [2,3]

1 College of Information Science and Engineering, Northeastern University, Shenyang 110819, China
2 State Key Laboratory of Intelligent Optimized Manufacturing in Mining & Metallurgy Process, Beijing 102628, China
3 BGRIMM Technology Group, Beijing 102628, China
* Correspondence: zou_gb@bgrimm.com; Tel.: +86-10-5906-9777; Fax: +86-10-5906-9797

Abstract: Mineral particle size is an important parameter in the mineral beneficiation process. In industrial processes, the grinding process produces pulp with qualified particle size for subsequent flotation processes. In this paper, a hierarchical intelligent control method for mineral particle size based on machine learning is proposed. In the machine learning layer, artificial intelligence technologies such as long and short memory neural networks (LSTM) and convolution neural networks (CNN) are used to solve the multi-source ore blending prediction and intelligent classification of dry and rainy season conditions, and then the ore-feeding intelligent expert control system and grinding process intelligent expert system are used to coordinate the production of semi-autogenous mill and Ball mill and Hydrocyclone (SAB) process and intelligently adjust the control parameters of DCS layer. This paper presents the practical application of the method in the SAB production process of an international mine to realize automation and intelligence. The process throughput is increased by 6.05%, the power consumption is reduced by 7.25%, and the annual economic benefit has been significantly improved.

Keywords: machine learning; mineral particle size; hierarchical intelligent control; LSTM; CNN

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1. Introduction

With the continuous depletion of resources and the increasing pressure of environmental protection and production costs, the production mode of mining enterprises is changing from an extensive production mode driven by human experience to an intelligent production mode driven by knowledge and data. The popularization of basic industrial process automation technology and the rapid development of big data and intelligent control technology also provide basic conditions and technical support for the intelligent operation of mineral processing [1,2]. More and more production problems that are difficult to solve by traditional methods need to be solved by artificial intelligence methods such as machine learning [3,4].

In recent years, with the improvement of computer performance, the rise of intelligent computing, and the development of AI algorithms such as machine learning and intelligent perception, machine learning technology has become a universal technology that can be used in all fields [5]. Machine learning, big data, expert systems, industrial internet, and other artificial intelligence have achieved practical applications from theoretical research, and the integration of applications in industrial scenarios shows great potential [6–10]. The industrial artificial intelligence technology represented by machine learning and intelligent perception has made breakthroughs and has been successfully applied in many fields, especially the image processing technology based on deep convolution networks, which has been increasingly applied in industrial process control, fault detection, key parameter acquisition of complex industrial systems [11–18] and other fields. Mou et al. introduced the generation antagonism network (GAN) for soft sensor modeling, established an innovative hybrid mechanism based on GAN and a data-driven soft sensor framework, and evaluated the effectiveness of the method in the industrial case of predicting the thermal deformation of the air preheater rotor of power plant boilers [19]. Wensi Ke et al. developed an LSTM-based deep neural network structure as a soft sensing method with strong nonlinearity and dynamics in the processing process and verified the effectiveness of the improved modeling method through the benchmark test of the sulfur recovery unit [20]. Yan proposed a Bayesian network (BN) based modeling and operational adjustment method is investigated [21].

Africa is rich in copper, cobalt, and other mineral resources. Because most of them are open-pit mining, the climate characteristics in the dry season and rainy season are obviously different, leading to large fluctuations in raw material properties, such as particle size and mineral composition. The existing control methods based on the determination of models and parameters have problems such as large parameter drift and weak applicability, which pose challenges to the production control of the SAB process. This is also a common problem facing the resource development of the African continent.

This paper focuses on the control problems for particle size in the SAB process of a copper concentrator in Africa. The layered intelligent control method based on machine learning is used to solve the above control problems. In the machine-learning layer, the long short memory neural network (LSTM), convolutional neural network (CNN), and other artificial intelligence technologies are used to solve the multi-source ore blending prediction and the intelligent classification of working conditions in dry and rainy seasons, Then, the intelligent expert control system for ore feeding and the intelligent expert system for semi-autogenous ball mill are used to coordinate the control of SAB process production and intelligently adjust the control parameters of DCS layer. This method has successfully improved SAB process production indicators and increased economic benefits.

2. SAB Process

2.1. SAB Process in Africa

Plant M is located in Africa, with a daily processing capacity of 10,000 tons. The SAB process is adopted for ore grinding and classification. As shown in Figure 1, The coarse ore pile is transported to the semi-autogenous mill (SAG mill). SAG mill ore discharge is screened by drum screen, and the hard stones on the screen are transported to the SAG mill by belt. The undersized slurry enters the grinding pump tank and is pumped to one group of hydrocyclones. The hydrocyclone grit returns to the ball mill for grinding. The ball mill discharge enters the grinding pump tank, and the hydrocyclone group finally forms a closed circuit. The cyclone overflows into the flotation operation. The fineness of the grinding product is −0.074 mm, accounting for 66%, and the pulp concentration is 32%, entering the downstream production process. The stability of the SAB process product production index seriously affects the production of downstream production processes and even affects the production efficiency of the entire concentrator. SAB process urgently needs to adopt automation and intelligent technology to control production stably.

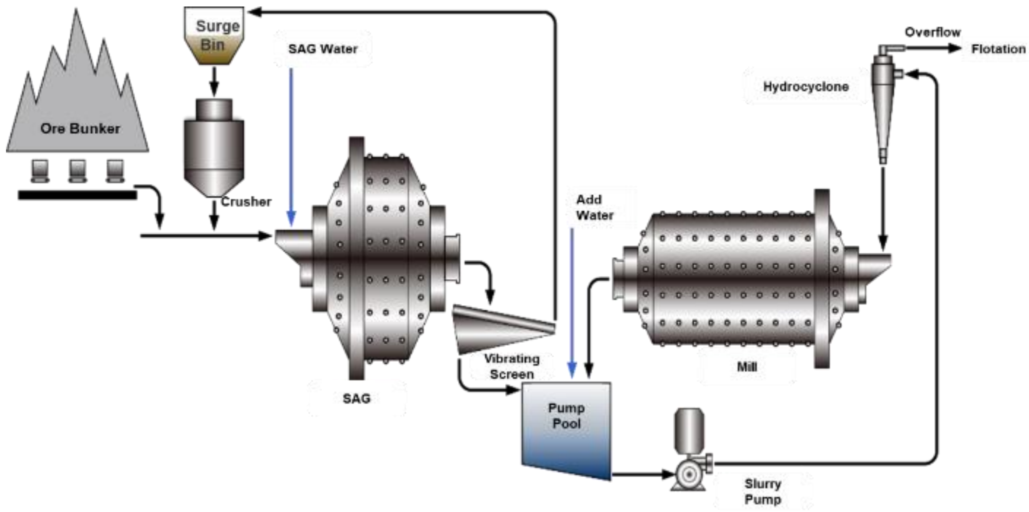

Figure 1. SAB process flowchart of Plant M.

2.2. Analysis of Operation Problems

For the SAB process of Plant M, due to the variable operating conditions of SAG grinding equipment, the operating parameters, such as power and axial pressure, vary greatly with different operating conditions. During the process operation, it is necessary to make targeted adjustments according to the change of working conditions in time to ensure that the main equipment operates in the best state. The operator is inexperienced, so it is difficult for the operator to accurately judge the operation status of the grinding production process, and cannot make correct production decisions and operate at the correct time point in time, thus affecting the overall operation efficiency and stability of the process. Different experiences and habits of different production operators will also lead to fluctuations in process indicators and equipment status between different production shifts, affecting the overall stability of the concentrator production. Due to the complex source, the raw ore obtained in the mining process is a mixture of copper sulfide and copper oxide. The mixing ratio of the two changes rapidly, resulting in large changes in hardness, lump powder ratio, and grindability of raw ore. The local climate conditions lead to obvious differences between the precipitation in the dry season and rainy season, and the open-air configuration of the grinding material pile leads to a large fluctuation of the raw ore water content with the seasons. If the ore-feeding fluctuation is not controlled, it will bring great disturbance to the system operation, making the grinding and classification process and grinding product quality fluctuate in a large range.

Due to the above characteristics, especially the problems caused by multi-source ore blending, such as the fluctuation of ore properties and the change of working conditions in dry and rainy seasons, which are difficult to solve by traditional control methods. It is also difficult to operate large equipment such as the SAG mill/ball mill stably in Plant M. As shown in Figure 2, the throughput of the SAG mill changes greatly, the main motor current of the SAG mill fluctuates frequently, and the main bearing pressure changes constantly, reflecting that the production of the SAG mill is difficult to stabilize. Production indicators such as particle size distribution and concentration of mill product will fluctuate violently, seriously affecting the production of downstream processes.

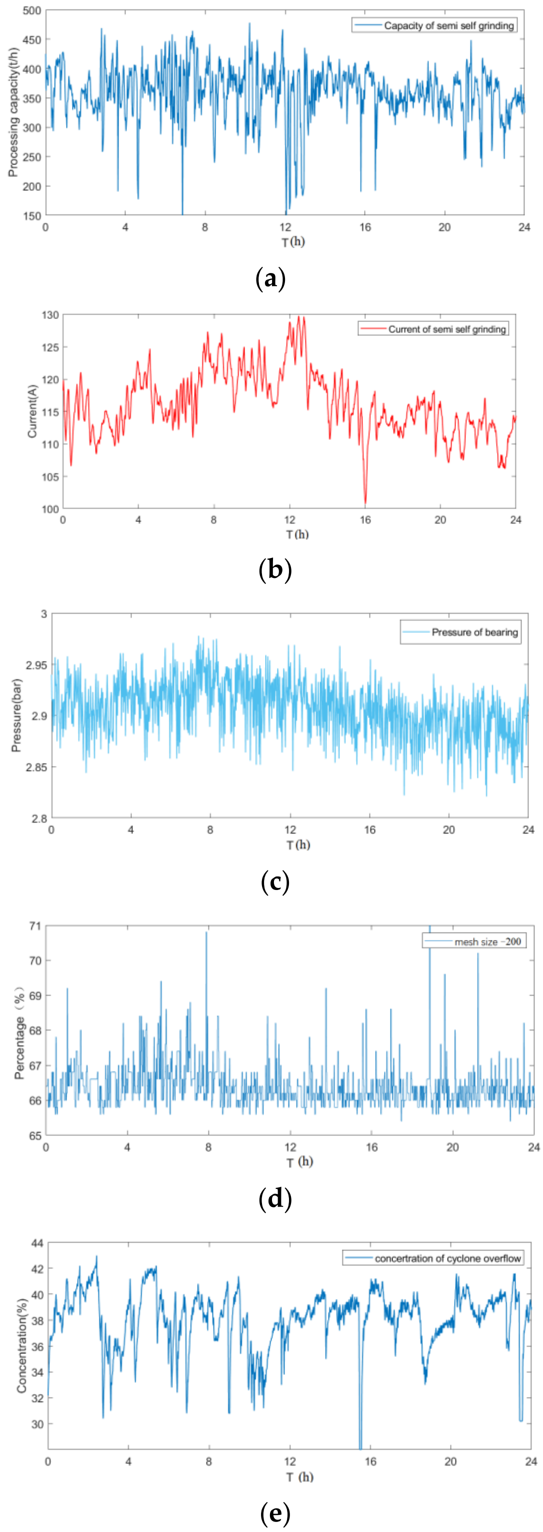

Figure 2. Difficulty in stabilizing the industrial grinding process. (**a**) Throughput of SAG Mill. (**b**) Current of SAG mill. (**c**) Pressure of bearing. (**d**) Percentage of mesh size (−200). (**e**) Concentration of cyclone overflow.

3. SAB Process Hierarchical Intelligent Control Method

3.1. Hierarchical Intelligent Control Structure

Machine learning is a research hotspot of industrial artificial intelligence. Its theory and method have been widely used to solve complex problems in engineering applications and scientific fields. Aiming at the problems that are difficult to solve by traditional control methods, such as the change of ore property of this process and the different working conditions in dry and rainy seasons, a layered intelligent control method of the SAB process based on machine learning is proposed, as shown in Figure 3.

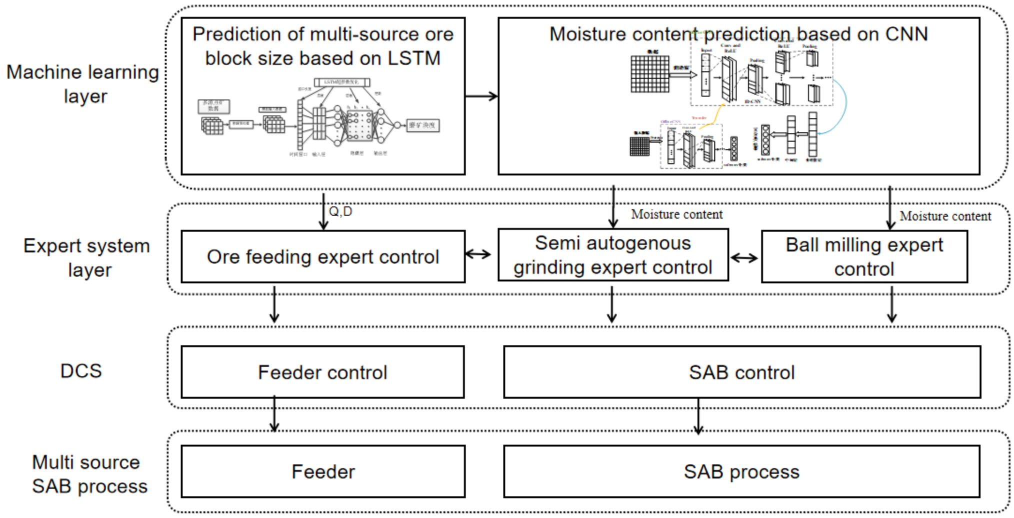

Figure 3. Hierarchical intelligent control of SAB process based on machine learning.

In the machine-learning layer, the subsequent semi-autogenous grinding and ball milling processes fluctuate dramatically due to the change of ore-feeding properties due to multi-source ore blending. In this paper, the LSTM-based semi-autogenous grinding ore-feeding block size prediction method is used to provide block size prediction information for intelligent expert control of ore. As the dry and rainy seasons lead to the change of mineral moisture, which affects the control parameters of semi-autogenous grinding and ball milling, the CNN-based intelligent classification of dry and rainy season working conditions is adopted to predict the classification of current working conditions online, adjust the current working condition parameters intelligently, and provide them to the semi-autogenous grinding expert control system and ball milling expert control system.

In the expert system layer, the intelligent expert control of ore feeding adopts the expert control method based on fuzzy rules. According to the prediction information of mineral property, the system intelligently adjusts the ore-feeding block size and ore quantity. The semi-autogenous grinding expert control and ball milling expert control adopt the CBR expert control method based on real-time compensation. According to the working condition parameters intelligently adjusted, the SAG mill and ball mill loads are intelligently coordinated, and the control parameters of the DCS layer are adjusted.

3.2. Machine Learning Layer

3.2.1. LSTM-Based Prediction Method for Feeding Lump Size of SAG

The precise control of ore feeding is the premise of efficient and stable operation of SAG and also the basis of the whole grinding intelligent control. For semi-autogenous grinding ore feeding, its specific control objectives include the stability of the ore-feeding amount and the stability of the ore-feeding lump size. Due to ore blending at multiple sources, the rock size in feed ore to the SAG mill will fluctuate, affecting the production stability of subsequent ball milling equipment. If the fragmentation of SAG mill input ore can be predicted according to the production data, the fragmentation change can be predicted in time when the working conditions are shifted due to multi-source ore, and the expert control system of the SAG mill can be guided to quickly adjust and reach the new set value, which is conducive to the stability of the whole system.

There are four ore feeders at the bottom of the raw ore bin. The location of each feeder is different. The corresponding storage height and ore fragmentation from feeders are also different and will change with the production process. The ore fragmentation shows obvious time-varying and nonlinear features. According to experts' experience and knowledge, the variables that can be detected online and have a great impact on the block size are selected, as shown in Table 1.

Table 1. Online detection variables of SAG.

No.	Variable Name
1	1# Belt frequency
2	2# Belt frequency
3	3# Belt frequency
4	4# Belt frequency
5	Feedrate of SAG mill
6	Current of SAG mill
7	Water feedrate of SAG mill
8	Pressure of SAG mill bearing
9	SAG mill 2# Belt current

Through the combination and verification of manual belt sampling and screening + video image manual marking division, the actual ore lump size on the semi-autogenous grinding feeding belt in a period of time can be quickly obtained. The long short memory neural network is used to train the prediction model of the ore block size for semi-autogenous grinding. The LSTM training network used in this paper is shown in Figure 4.

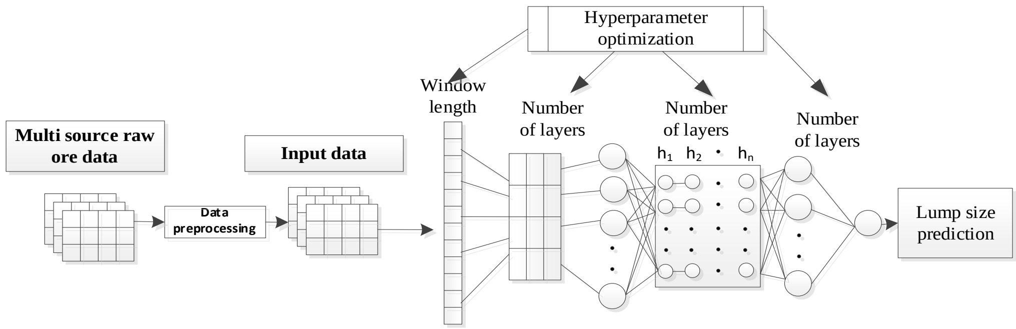

Figure 4. Prediction of grinding fragmentation based on LSTM.

In the process of LSTM modeling, the problem of overfitting often occurs. The model network structure is too complex, which exceeds the actual problem. It performs well in the training set but performs poorly in the test set and has poor generalization performance. Therefore, Dropout is used to reduce the overfitting phenomenon when training the network. Adam optimizer is selected for updating model parameters. The RMSE and ARGE are calculated by the formulas in [22–24].

The LSTM network is a deep neural network with many superparameters for predicting the feeding lump size of the SAG mill. Since all neural networks have an input layer and an output layer, the complexity of the deep learning model mainly depends on the number of hidden neurons and the number of neurons in each layer, which is the main superparameter of the deep learning model. In addition to the network structure, the LSTM network model also has this time window size, which is more parameters and more complex to optimize than the general deep neural network. The superparameter learning method with the following structure is used to optimize the network parameters.

As shown in Figure 5. SQP algorithm is used to optimize the superparameters of the prediction model for the feed size of the SAG mill. The optimization problem is expressed as follows [25]:

$$\begin{cases} \min f(x) \\ subject\ to\ g_i(x) \le 0\ (i = 1,2,\ldots,m_p) \\ \qquad\qquad g_i(x) = 0\ (i = m_p + 1,\ldots,m) \end{cases} \tag{1}$$

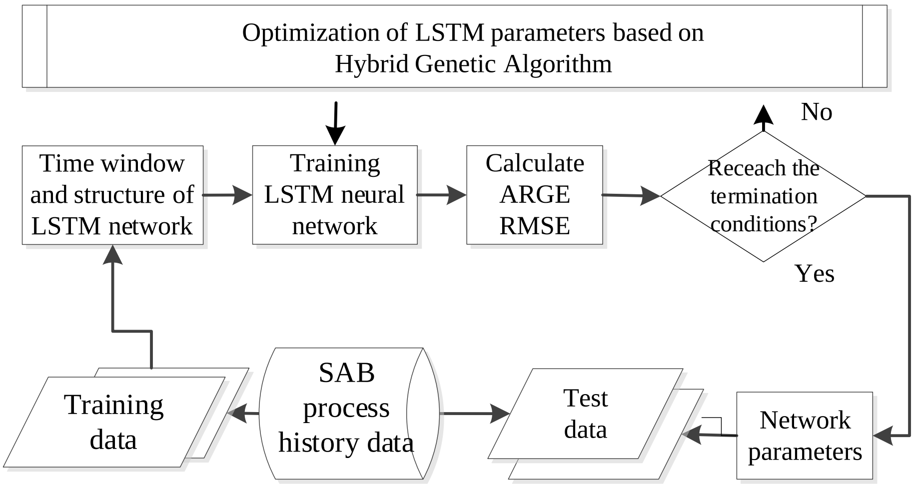

Figure 5. Optimization of LSTM parameters based on hybrid genetic algorithm.

For the soft-sensing detection of the feeding lump size of the SAG mill, GA and HGA are used to optimize the hidden layer of the LSTM network, the unit number of the hidden layer, and the Dropout probability. In order to ensure the validity of the comparison of model performance results, the superparameter settings that do not involve optimization should be the same. In the HGA optimization experiment, the modeling based on GA-LSTM is first carried out. The initial population size of the genetic algorithm [1] is set to 30, the crossover rate is 0.5, the mutation rate is 0.1, and the total number of iterations is set to 20. When the genetic algorithm is used to optimize the super parameters of the LSTM network, the optimal fitness function of the optimal chromosome in the population, namely the RMSE value of the LSTM network on the test set, gradually converges with the increase of iteration times. The lump size prediction effect of SAG based on LSTM is shown in Figure 6.

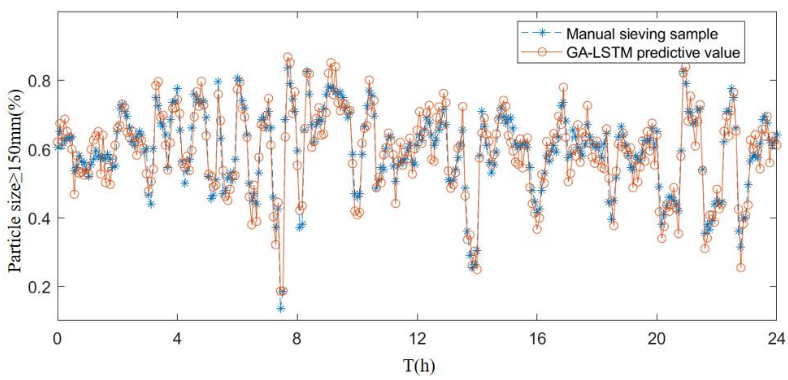

Figure 6. Lump size prediction of SAG mill feed.

3.2.2. Classification of Moisture Content in Dry and Rainy Seasons Based on CNN

Due to the local climate conditions, the precipitation in the dry season is obviously different from that in the rainy season, while the open pit configuration of the grinding material pile results in a large fluctuation of the raw ore water content with different seasons. In the dry season, the water content of raw ore is about 8%–10%, while in the rainy season, when the precipitation is large, the water content of raw ore can reach about 15%. This brings great interference to the grinding production control and affects the control effect of the optimal control system in the rainy season. In order to improve the adaptability of the control system, it is necessary to realize the adaptive control algorithm parameters.

A total of 24,500 pieces of data covering 24 months, as shown in Table 2, including the dry season and rainy season. Moreover, 15,000 pieces of data were used for modeling training, 5000 pieces of data were used for modeling testing, and 4500 pieces of data were used for modeling validation.

Table 2. Data variables for CNN training.

No.	Variable Name
1	Mesh size (Video extraction)
2	Feedrate of SAG mill
3	Water feedrate of SAG mill
4	Current of SAG mill
5	Bearing pressure of SAG mill
6	Current of ball mill
7	Bearing pressure of ball mill
8	Water feedrate to sump
9	Pressure of cyclone
10	Flow of cyclone
11	Concentration of cyclone
12	Particle size of cyclone overflow

A CNN network using VGG-16 structure [26,27], with five segments connected in series by multiple 3 × 3 convolutional kernels. The maximum pooling layer with a size of 2 × 2 is connected after each convolutional segment. The network scales the feature map through the pooling layer, with three fully connected layers and one softmax layer connected at the end [28]. The network structure in Figure 7 is used to classify the data during the dry and rainy seasons, and the classification results are combined with manual labeling, as shown in Figure 8.

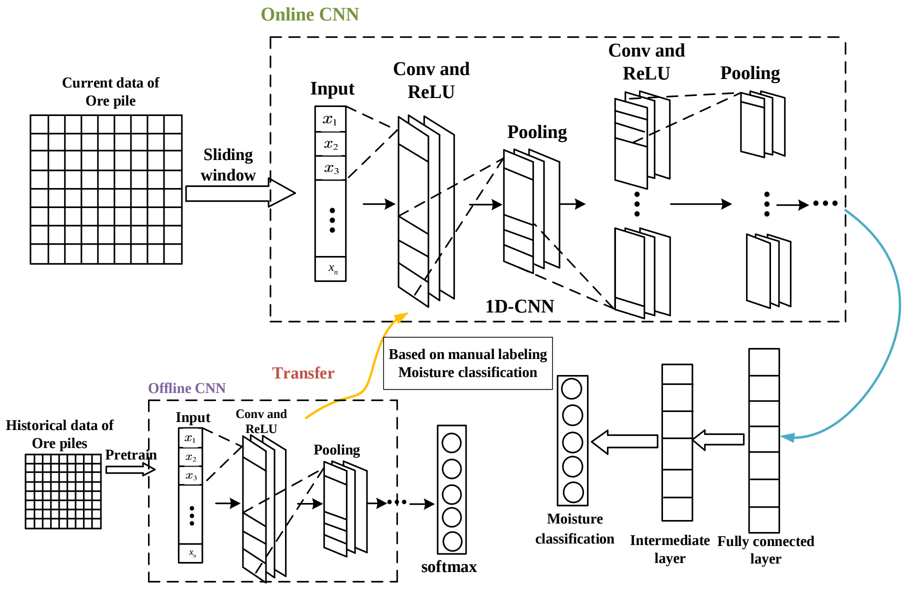

Figure 7. Classification of moisture content in dry and rainy seasons based on CNN.

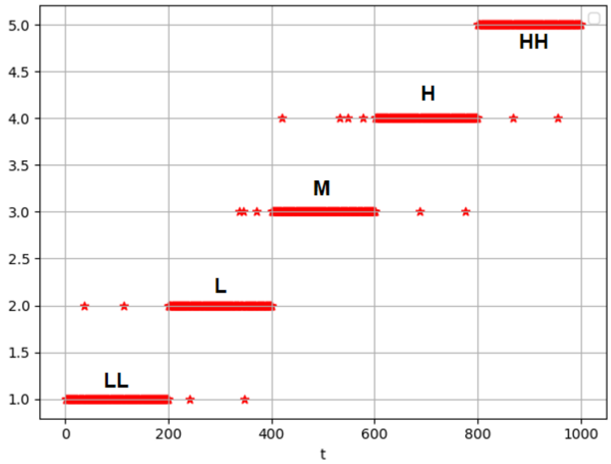

Figure 8. Results of classification of moisture content in dry and rainy seasons based on CNN.

3.3. Expert Control Layer

3.3.1. Feeding Expert Control

The precise control of ore feeding is the premise of efficient and stable operation of the SAG mill as shown in the Table 3 and also the basis of the whole grinding intelligent control. For semi-autogenous grinding ore feeding, its specific control objectives include two aspects: the stability of the ore-feeding amount and the stability of ore-feeding particle size distribution. In detail, one is to maintain the stability of mineral feeding materials under normal working conditions, and another is to quickly adjust and reach the new set value when working conditions migrate, which is conducive to the stability of the entire system.

Table 3. Online detection variables of SAG mill.

IF	THEN
LL	Parameter Group 1 of Expert control layer
L	Parameter Group 2 of Expert control layer
M	Parameter Group 3 of Expert control layer
H	Parameter Group 4 of Expert control layer
HH	Parameter Group 5 of Expert control layer

Difficulties of intelligent feeding include large system lag, sometimes variable storage and measuring tools in the silo, differences among feeders, and sudden occurrence of various abnormal conditions on-site. As for Plant M, there are four feeders at the bottom of the raw ore bin. The location of each feeder is different, and its corresponding storage height and ore block size are different and change with the production process. The ore-feeding capacity and ore block size show obvious time variation and difference. The distance between the feeder and the belt scale (measuring mechanism) is about 200 m, with a delay of about 2 min. In the rainy season, the feeder downport is easy to be blocked. At this time, the operators must stop the corresponding feeder immediately and start a new feeder to ensure the continuity of production. In actual production, materials in raw ore are mixed with various ores with different copper grades and particle sizes according to the feedback scheduling of the flotation process. Aiming at the actual problems on-site, the feeding expert control system compensates for the dynamic changes of the feeding process through the LSTM-based model of the feeding process and conducts real-time control on the amount and fragmentation of SAG mill feed to ensure the stability of grinding production as shown in Figure 9.

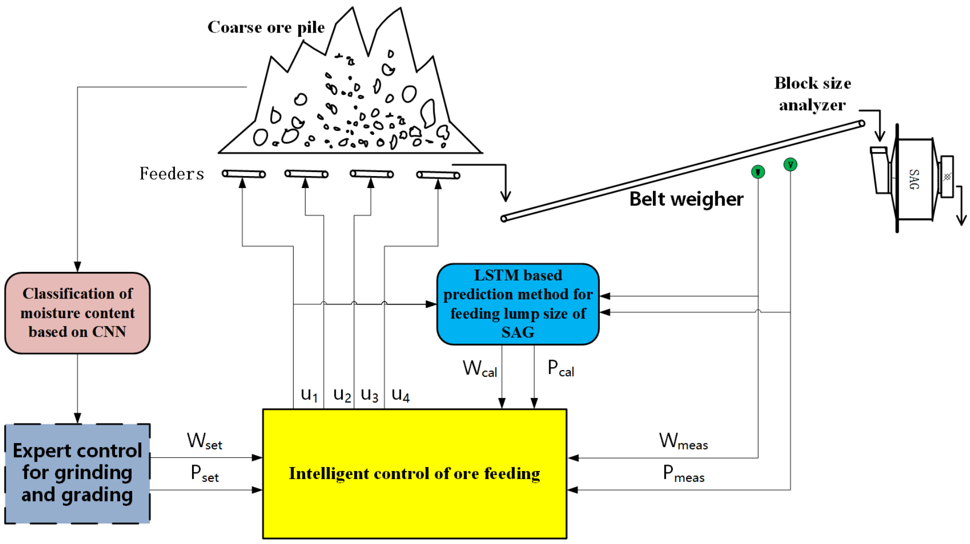

Figure 9. Intelligent control of ore-feeding plus compensation module.

If the ore-feeding capacity of the ith feeder ($1 \leq i \leq 4$) is k_i, the proportion of large blocks is p_i, its frequency value is u_i, the prediction value of ore-feeding amount is W_{cal}, and the prediction value of the proportion of large blocks is P_{cal}, then:

$$\begin{cases} \sum_{i=1}^{4} k_i \cdot u_i = W_{cal} \\ \sum_{i=1}^{4} p_i \cdot k_i \cdot u_i = P_{cal} \cdot W_{cal} \\ u_{min} \leq u_i \leq u_{max} \end{cases} \tag{2}$$

When there is a deviation between the actual value W_{means} of the ore-feeding amount measured by the ore-feeding belt scale and the P_{meas} measured by the ore lump analyzer and the set value W_{set} of the ore-feeding amount and the set value P_{set} of the ore-feeding lump proportion given by the grinding and classification expert control, the adjustment amount of the feeder frequency can be calculated by the increment method:

$$\begin{cases} \sum_{i=1}^{4} k_i \cdot \Delta u_i = W_{meas} - W_{set} \\ \sum_{i=1}^{4} p_i \cdot k_i \cdot \Delta u_i = P_{meas} \cdot W_{meas} - P_{set} \cdot W_{set} \\ -u_{max} \leq \Delta u_i \leq u_{max} \\ u_{min} \leq u_i + \Delta u_i \leq u_{max} \end{cases} \tag{3}$$

In the actual control, according to the coarse and fine classification of the ore feeder's blanking block size, the frequency of one coarse and one fine pair of ore feeders can be adjusted each time, so the above equation can be degenerated into a two-dimensional linear equation, which can be solved quickly. When the ore-feeding frequency is lower than the lower limit or higher than the upper limit, poll other ore-feeding port matching schemes or turn on/off the feeder.

When it is necessary to open or close the feeder, in order to ensure that the belt materials are not stacked and empty, the physical position of the ore-feeding mouth and the speed of the transmission belt are measured, and the switching sequence and time of the feeder at each ore-feeding mouth are precisely controlled, so as to realize the continuous and stable transmission of the mineral material flow on the ore-feeding belt.

In view of the large delay (2 min) of feeding machine blanking and belt weigher measurement value, a large interval sampling control is adopted. The cycle of the controller is greater than the maximum lag time of each feeder with state change in the last control cycle plus the maximum adjustment time of the feeder (5 s~10 s). Because the control effect of the regulator output is unknown within the lag time. The basic idea of large interval sampling is to wait for a period of time after one adjustment until the end of the adjustment process, and the measurement result of the belt scale can fully reflect the real ore-feeding amount before the next adjustment so as to avoid false adjustment due to misjudgment, resulting in closed-loop system oscillation or instability. Through large interval sampling control, it can realize stable ore feeding when switching feeder and adjust in place as soon as possible in case of error.

The effect after the expert control system is shown in Figure 10. The fluctuation range of fragmentation is reduced, and the production process is more stable, meeting the production index requirements.

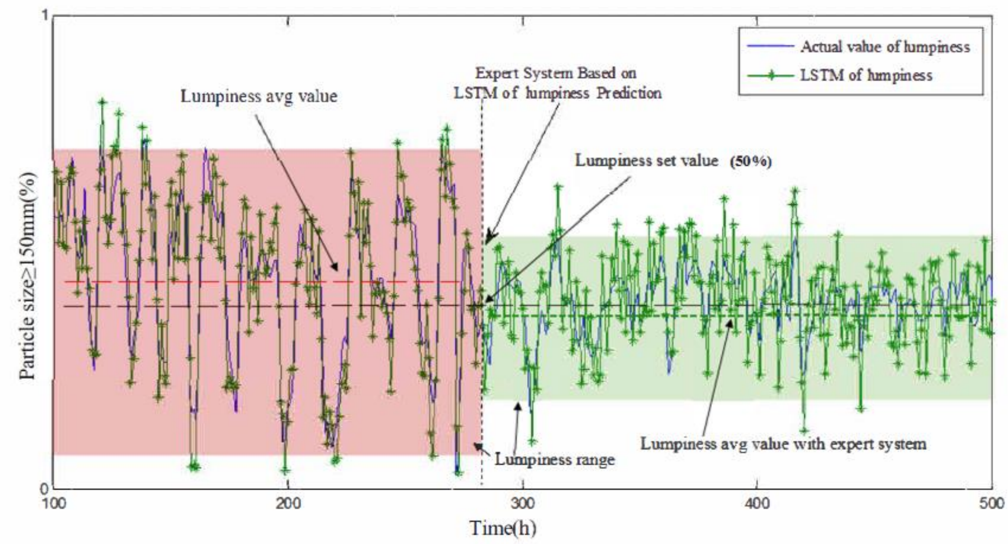

Figure 10. The stability of feeding lump size of the SAG controlled by experts.

3.3.2. CBR Expert Control Method

According to the characteristics of the new problem, the case-based reasoning process first compares the relevance of the historical cases in the case base and then selects one or several cases that meet a certain degree of similarity from the case base. Similar case solutions are modified to be the solutions to new problems. And through the effect of solving the problem, it is decided whether to store the case of the new problem into the case base so as to solve the following problems. Some edge conditions cause similar cases to be found in the case retrieval process, or the case matching similarity is low. So, these cases need to be translated and interpreted through the previously set production rule base and solved through the pre-chain rules, which are applied to the scene, solving the production misoperation when the case matching similarity is not high.

Because there is a certain difference between the retrieved case and the current working condition, there is also a certain difference between the case solutions. Therefore, the case solution cannot be directly used as the solution to the current working condition. In order to further improve the accuracy of the model, the RBF neural network method is used to establish an incremental compensation model to compensate for the retrieved case solution.

4. Application Effect and Analysis

4.1. Intelligent Control System

As shown in Figure 11. The Grinding Process Master software(BPM-G v1.0) has been developed by using the above technologies. In this SAB process, the closed-loop control and intelligent optimization of operating variables such as ore feed rate, water feed rate, and sand pump frequency have been realized, ensuring the safe, stable, and efficient operation of the entire production process. At present, the SAB process has been in actual operation for more than one year.

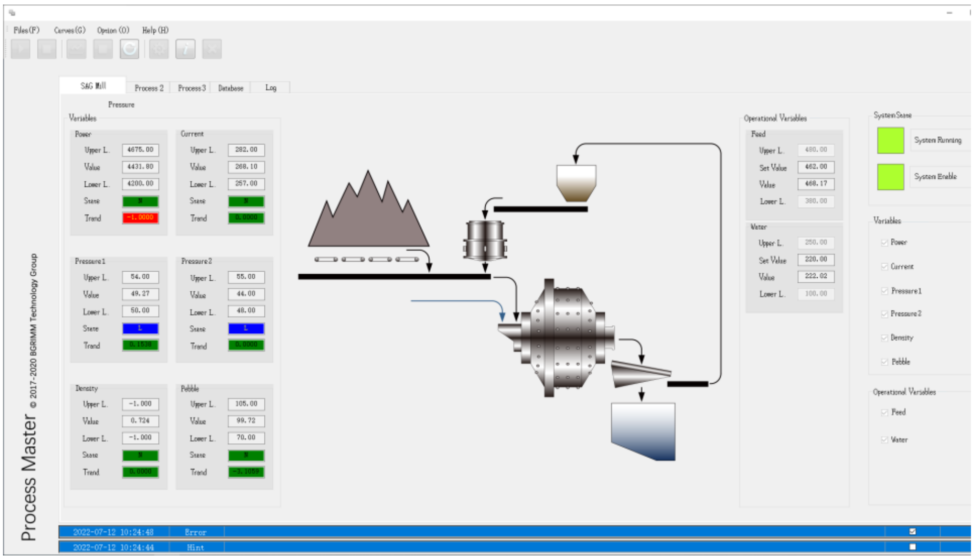

Figure 11. The stability of feeding lump size of the SAB controlled by experts.

4.2. Application Effect

After the application of the grinding optimization control system, the closed-loop automatic control of the grinding and classification process is realized, the intensity of manual operation is reduced, the dependence on operating experience is reduced, and labor productivity is improved. Based on stabilizing the production process and reducing the abnormal disturbance in the production process, the system processing capacity is increased, and the production unit consumption is reduced.

Through real-time intelligent diagnosis of production process operation status, the system timely and reasonably adjusts production operation variables to ensure the stability of production equipment operation status and production process parameters. After the system is put into use, the fluctuations of key production process indicators are reduced by more than 20%. The grinding expert system stabilizes the operation parameters of each piece of equipment in the SAB process within a reasonable range according to different ore sources. The stability of the process operation ensures the stability of the grinding and classification of product quality. The grinding particle size is more concentrated in the optimal mesh size area, as shown in Figure 12.

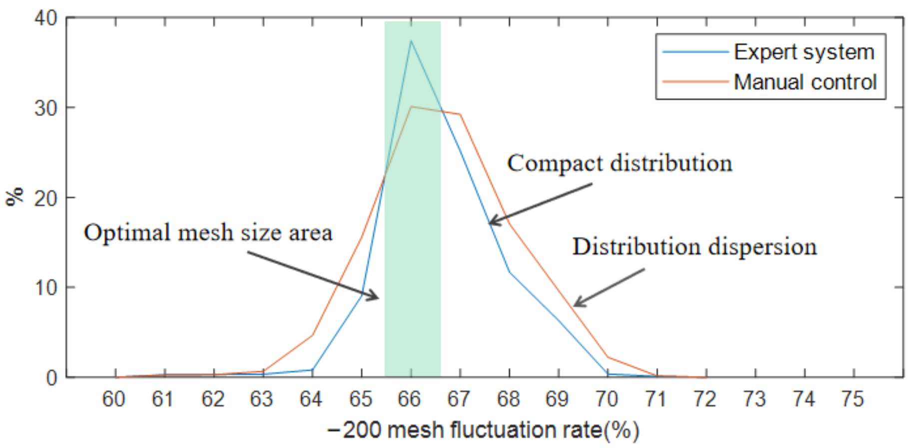

Figure 12. Particle size distribution statistics of grinding products.

As shown in Table 4, after the system is put into use, the grinding expert system can sensitively capture the changing trend of the key operating parameters of the SAG mill, adjust the efficiency in time when the working conditions change, and ensure the SAG mill to operate in a reasonable load state range to the greatest extent. On the premise of stabilizing the working conditions and ensuring the process indicators, the production efficiency of the process is improved. The average processing capacity of grinding production increased by 6.05%.

Table 4. Statistical comparison of production parameters on 6 months data.

Variable Name	Unit	Before	After	Improve
Throughput fluctuation rate	%	33.81%	17.72%	−47.6%
Current fluctuation rate of main motor	%	10.39%	5.89%	−43.3%
Bearing pressure fluctuation rate	%	10.78%	7.01%	−35.0%
−200 mesh fluctuation rate	%	6.72%	3.45%	−48.7%
Concentration fluctuation rate	%	12.93%	8.39%	−35.1%

By stabilizing the operation state of the production process, the system ensures that the process always operates in a state of high economic benefits under different ore properties, reduces the unit production consumption, and reduces the wear of the lining plate. According to the statistical data of the grinding system, including process parameter indicators such as unit efficiency and energy consumption (power consumption, ball consumption), the power consumption per ton of mill ore decreased by 7.25% on average, increasing the total amount of ore processing within the service life of a single set of liner plates.

5. Conclusions

Aiming at the control problems of mineral particle size in the SABC grinding process, this paper proposes an intelligent expert control method of the SABC process based on a hybrid model. A hybrid model of SVR and mechanism model is adopted to realize the online perception of overflow fineness. The adaptability of the expert rule base is improved by intelligent correction of uncertainty, and then combined with the experience of field operation experts, intelligent optimization control of overflow fineness and unit power consumption is realized.

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References

1. Zou, G.; Zhou, J.; Li, K.; Zhao, H. An HGA-LSTM-Based Intelligent Model for Ore Pulp Density in the Hydrometallurgical Process. *Materials* **2022**, *15*, 7586. [CrossRef]
2. Fan, C.; Ren, L.; Zhang, Y.; Bao, S. Grinding effect of sodium silicate on muscovite and its mechanism analysis. *Miner. Eng.* **2023**, *199*, 108106. [CrossRef]
3. Sadr, H.; Pedram, M.M.; Teshnehlab, M. Multi-View Deep Network: A Deep Model Based on Learning Features From Heterogeneous Neural Networks for Sentiment Analysis. *IEEE Access* **2020**, *8*, 86984–86997. [CrossRef]
4. Tian, Y.H. Artificial Intelligence Image Recognition Method Based on Convolutional Neural Network Algorithm. *IEEE Access* **2020**, *8*, 125731–125744. [CrossRef]
5. Jiang, Y.; Yin, S.; Dong, J.; Kaynak, O. A review on soft sensors for monitoring, control, and optimization of industrial processes. *IEEE Sens. J.* **2020**, *21*, 12868–12881. [CrossRef]
6. Kadlec, P.; Gabrys, B.; Strandt, S. Data-driven Soft Sensors in the process industry. *Comput. Chem. Eng.* **2009**, *33*, 795–814. [CrossRef]

7. Lu, Y.; Lu, G.M.; Lin, R. SRGC-Nets: Sparse Repeated Group Convolutional Neural Networks. *IEEE Trans. Neural Netw. Learn. Syst.* **2019**, *31*, 2889–2902. [CrossRef] [PubMed]
8. Li, K.; Daniels, J.; Liu, C.; Herrero, P.; Georgiou, P. Convolutional Recurrent Neural Networks for Glucose Prediction. *IEEE J. Biomed. Health Inform.* **2020**, *24*, 603–613. [CrossRef] [PubMed]
9. Dai, J.; Chen, N.; Yuan, X.; Gui, W.; Luo, L. Temperature prediction for roller kiln based on hybrid first-principle model and data-driven MW-DLWKPCR model. *ISA Trans.* **2020**, *98*, 403–417. [CrossRef]
10. Kim, B.; Yuvaraj, N.; Preethaa, K.R.S.; Pandian, R.A. Surface crack detection using deep learning with shallow CNN architecture for enhanced computation. *Neural Comput. Appl.* **2021**, *33*, 9289–9305. [CrossRef]
11. Zhou, P.; Gao, B.; Wang, S.; Chai, T. Identification of Abnormal Conditions for Fused Magnesium Melting Process Based on Deep Learning and Multi-source Information Fusion. *IEEE Trans. Ind. Electron.* **2021**, *99*, 1.
12. Zhang, H.; Tang, Z.; Xie, Y.; Chen, Q.; Gao, X.; Gui, W. Feature Reconstruction-Regression Network: A Light-Weight Deep Neural Network for Performance Monitoring in the Froth Flotation. *IEEE Trans. Ind. Inform.* **2020**, *17*, 8406–8417. [CrossRef]
13. Zhang, J.; Tang, Z.; Xie, Y.; Chen, Q.; Ai, M.; Gui, W. Timed key-value memory network for flotation reagent control. *Control Eng. Pract.* **2020**, *98*, 104360. [CrossRef]
14. Gao, F.; Ma, F.; Wang, J.; Sun, J.; Yang, E.; Zhou, H. Semi-Supervised Generative Adversarial Nets with Multiple Generators for SAR Image Recognition. *Sensors* **2018**, *18*, 2706. [CrossRef]
15. Hinton, G.E.; Salakhutdinov, R.R. Reducing the Dimensionality of Data with Neural Networks. *Science* **2006**, *313*, 504–507. [CrossRef] [PubMed]
16. Zhou, K.; Yang, C.; Liu, J.; Xu, Q. Deep graph feature learning-based diagnosis approach for rotating machinery using multi-sensor data. *J. Intell. Manuf.* **2022**, *34*, 1965–1974. [CrossRef]
17. Zhou, X.; Wang, Q.; Zhang, R.; Yang, C. A hybrid feature selection method for production condition recognition in froth flotation with noisy labels. *Miner. Eng.* **2020**, *153*, 106201. [CrossRef]
18. Zhang, H.; Tang, Z.; Xie, Y.; Yuan, H.; Chen, Q.; Gui, W. Siamese Time Series and Difference Networks for Performance Monitoring in the Froth Flotation Process. *IEEE Trans. Ind. Inform.* **2021**, *18*, 2539–2549. [CrossRef]
19. Mou, L.; Ghamisi, P.; Zhu, X.X. Deep Recurrent Neural Networks for Hyperspectral Image Classification. *IEEE Trans. Geosci. Remote Sens.* **2017**, *55*, 3639–3655. [CrossRef]
20. Ke, W.; Huang, D.; Yang, F.; Jiang, Y. Soft sensor development and applications based on LSTM in deep neural networks. In Proceedings of the 2017 IEEE Symposium Series on Computational Intelligence (SSCI), Honolulu, HI, USA, 27 November–1 December 2017. [CrossRef]
21. Yan, H.; Wang, F.; He, D.; Zhao, L.; Wang, Q. Bayesian Network-Based Modeling and Operational Adjustment of Plantwide Flotation Industrial Process. *Ind. Eng. Chem. Res.* **2020**, *59*, 2025–2035. [CrossRef]
22. Sherstinsky, A. Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) Network. *Phys. D Nonlinear Phenom.* **2020**, *404*, 132306. [CrossRef]
23. Pan, H.; Su, T.; Huang, X.; Wang, Z. LSTM-based soft sensor design for oxygen content of flue gas in coal-fired power plant. *Trans. Inst. Meas. Control* **2021**, *43*, 78–87. [CrossRef]
24. Alshwaheen, T.I.; Hau, Y.W.; Ass'Ad, N.; Abualsamen, M.M. A Novel and Reliable Framework of Patient Deterioration Prediction in Intensive Care Unit Based on Long Short-Term Memory-Recurrent Neural Network. *IEEE Access* **2020**, *9*, 3894–3918. [CrossRef]
25. Mansoornejad, B.; Mostoufi, N.; Jalali-Farahani, F. A hybrid GA–SQP optimization technique for determination of kinetic parameters of hydrogenation reactions. *Comput. Chem. Eng.* **2008**, *32*, 1447–1455. [CrossRef]
26. Gu, K.; Xia, Z.F.; Qiao, J.F. Deep dual-channel neural network for image-based smoke detection. *IEEE Trans. Multimed.* **2020**, *22*, 311–323. [CrossRef]
27. Xu, G.W.; Liu, M.; Jiang, Z.F.; Huang, C.X. Online fault diagnosis method based on transfer convolutional neural networks. *IEEE Trans. Instrum. Meas.* **2019**, *69*, 509–520. [CrossRef]
28. Fang, C.; He, D.; Li, K.; Liu, Y.; Wang, F. Image-based thickener mud layer height prediction with attention mechanism-based CNN. *ISA Trans.* **2022**, *128*, 677–689. [CrossRef] [PubMed]