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Design and Implementation of Machine Learning-based Monitoring System for Mineral Processing Flotation Reagent

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Abstract: Flotation, also known as froth flotation, is a method for separating minerals from powdered materials by altering their floatability through the use of flotation reagents. This paper proposes a flotation process control system for mineral processing based on machine learning. Addressing the issue of lack of precise detection methods in the flotation process of iron concentrate, a neural network regression method is used to predict the amount of reagents and the grade of the flotation concentrate. The flotation data in this paper come from the Key Laboratory of Multitechnology Resource Utilization of Bayan Obo Mine, Inner Mongolia Autonomous Region. The preprocessed data form the dataset used to create the production prediction model. The neural network model is constructed using the PyTorch deep learning framework. Finally, based on the established model, a comprehensive flotation dosing monitoring system is developed using the Django framework, which includes functions such as production indicator large screens, workshop personnel safety monitoring large screens, flotation reagent usage processing, flotation reagent procurement platform.

Keywords: Froth flotation; Neural network; Monitoring platform; Machine learning

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1. Introduction

The objective of mineral processing is to remove a large amount of gangue and harmful elements contained in the ore, thereby enriching the valuable minerals and separating coexisting useful minerals from each other to obtain one or more useful concentrate products. Froth flotation(flotation) is a method in which mineral powders are treated with flotation reagents to alter their floatability, allowing the targeted minerals to selectively adhere to bubbles, thus enabling the selection of the desired minerals. Flotation occupies a predominant position among various mineral processing methods and has a wide range of applications. It can process not only non-ferrous metal minerals (such as copper, lead, zinc, molybdenum, cobalt, tungsten, antimony ores, etc.) but also non-metallic minerals (such as graphite, barite, fluorite, apatite, feldspar, talc, etc.) and ferrous metal minerals (such as hematite, manganese, and titanium ores, etc.). Compared to other mineral processing methods, flotation has a high separation efficiency, capable of upgrading low-grade raw ores into high-grade concentrates, thus expanding the range of mineral resources. Flotation is particularly effective in treating finely disseminated ores, solving the recovery of valuable components in many fine mineral particles. Flotation automation is the new trend in mineral processing technology. Traditional flotation operations often rely on manual dosing, which results in inaccurate and untimely addition of reagents. Overdosing can lead to raw material waste and environmental pollution, while underdosing can result in insufficient reaction between reagents and minerals, reducing the yield of the final product [1–4].

1.1. Research background and significance

This project is a collaborative effort between the Cloud Computing and Big Data Laboratory of the School of Computer Science and Engineering at Dalian Minzu University and Baoshan Mining Company. The relevant data parameters for the project are sourced from Baoshan Mining Company's "Inner Mongolia Ore Flotation Desulfurization Experimental Study" project. Traditionally, mineral flotation processing has relied on manual control for related operations, requiring frontline operators to manually adjust reagent dosages and flotation tank liquid levels.[5]. However, this method has consistently faced issues of inaccuracy and untimeliness, sometimes failing to meet the technical indicators required by flotation processes. Errors in this process can also significantly impact production safety. Additionally, the production process involves the use of many highly toxic processing reagents, such as cyanides. Traditional monitoring methods require substantial human labor, such as deploying monitoring rooms and dispatch rooms to oversee personnel and vehicle movements in high-risk areas. This not only wastes human resources but also poses safety risks due to potential lapses in human supervision. Therefore, this paper integrates artificial intelligence and other computer technologies into the production process to enhance mineral processing indicators and ensure production safety.

1.2. Figures and tables

In recent years, with the continuous advancement of automation technology, the level of flotation automation and the addition of flotation reagents have been continuously improving. In the production process of adding flotation reagents, relying solely on manual dosing makes it difficult to accurately control the dosage and timely addition of reagents. The automated application of flotation reagents not only overcomes the shortcomings of manual adjustment but also reduces reagent consumption during the flotation process [6].

In 2001, Xu Deping, Wu Cuiping, and others conducted an analysis and research on the beneficiation parameters in coal slime beneficiation. They integrated computer software design and electromechanical control systems to develop a coal slime flotation pulp level meter and a coal slurry ash meter. This system achieves control over the flotation process by measuring the ash content of coal slime and subsequent data, using fuzzy control technology to adjust the flotation reagent dosage and flotation machine pulp level [7–9].

In 2022, Xu Zewei from Fenxi Mining South Coal Industry proposed solutions using sensor technology and PLC control technology to address the high control difficulty and low operational efficiency in the flotation process of premium coal. By using pressure sensors (liquid level height detection), slurry concentration sensors, ultrasonic flow meters, electromagnetic flow meters, and tailings ash detection devices to monitor key indicators in the coal beneficiation process, automated control of the coal beneficiation process was achieved [10].

In 2024, Zhang Hongchang, Mou Song, and other technical personnel used an engineering dosing system and DCS control system for data communication, achieving information interaction and detection between the scheduling department and data communication. This made the process of machine-assisted automated dosing more stable, bringing more direct benefits to the company.

2. Mechanism and process of mineral flotation

Ore is one of the crucial raw materials in the metal manufacturing industry. Mineral processing aims to maximize the separation of valuable minerals from gangue minerals to obtain high-grade concentrates and to recover coexisting valuable minerals as separate concentrates for their useful components. Among the modern mineral processing techniques, flotation and magnetic separation are the mainstream methods for mineral beneficiation.

2.1. Definition and calculation of ore grade

Ore grade refers to the amount of a specific metal or useful component contained within the ore, typically expressed as a percentage. For precious metals (such as gold, silver, or gemstones), the grade is expressed in g/t or g/m^3. The grade of the ore is determined by sampling and assay results. Depending on the properties of the ore, it can be classified into raw ore grade, concentrate grade, and tailings grade. The raw ore grade (denoted as α) represents the percentage of metal content in the raw ore that enters the processing plant. It is an indicator of raw ore quality and a fundamental data point for the metal balance of the processing plant. The concentrate grade (denoted as β) indicates the percentage of metal content in the concentrate, reflecting the quality of the concentrate. The tailings grade (denoted as θ) represents the percentage of metal content in the tailings, indicating the metal loss during the beneficiation process.

Processing plants typically assay the concentrate grade once every shift (12 hours). The concentrate yield and grade of each shift vary. Let the yields of three shifts be Q_1, Q_2, and Q_3 and their respective grades be β_1, β_2 and β3. The average grade of the three shifts can be calculated as follows:

$$\overline{\beta} = \frac{Q_1\beta_1 + Q_2\beta_2 + Q_3\beta_3}{Q_1 + Q_2 + Q_3} \times 100\%$$

In the statistical reports of the processing plant, there is a cumulative grade section. The cumulative grade is calculated similarly to the average grade but is a cumulative process:

$$\overline{\beta_i} = \frac{\mathrm{Qi} - 1 \quad \times \beta \mathrm{i} - 1 \quad + \mathrm{qi} \quad \times \beta \mathrm{i},\ \mathrm{day}}{\mathrm{Qi}}$$

2.2. Basic concepts of flotation

Flotation, fully known as froth flotation, is a mineral processing method that relies on the differences in the chemical properties of mineral particle surfaces. By utilizing the buoyancy of bubbles in the slurry, it achieves the separation of minerals. Modern flotation operations mainly include four processes: grinding, slurry conditioning with reagents, flotation separation, and product handling. The froth product and tailings from flotation undergo dewatering separation, as shown in **Figure 2.1**.

Compared to other mineral processing methods, flotation has higher separation efficiency. It can upgrade low-grade ores into high-grade concentrates, expanding the utilization scope of minerals. This allows for the development and utilization of low-grade deposits that were previously considered unexploitable into high-quality deposits. Flotation is particularly effective for processing fine and ultra-fine minerals. Due to the fine particle size and minimal density differences, gravity separation is difficult for these minerals. However, by adjusting with reagents and mechanical methods based on the different surface activities of the minerals, flotation can effectively separate valuable minerals from waste materials.

3. System requirements analysis

3.1. Functional requirements

The primary function of the mineral processing flotation reagent dosing system is to monitor and analyze the indicators of the mineral processing flotation process, predict the grade of the concentrate, and determine the optimal reagent dosage. The system also visualizes the collected data, displaying it on the front-end interface using alert notifications and statistical charts to guide flotation workshop operators in adjusting reagent dosages. Given that flotation reagents are generally toxic, the factory imposes strict standards on protective labor measures for production personnel and the management of vehicles and personnel in hazardous areas. The system processes video information received from cameras frame by frame, performs image recognition on the footage, uploads detected hazardous information to the database, and displays it on the corresponding front-end interface.

(1) Production indicator display screen

The data display module aggregates the on-site technical indicators from the database onto the data display screen. On this screen, one can view the status of reagent dosages, the addition of reagents, the predictions of concentrate and tailings grades, and the types of reagents currently in use. By visualizing the data from the database for on-site operators and displaying the estimated reagent dosages for the next stage, the system can guide the reagent dosing process.

(2) Workshop personnel safety monitoring display screen

The workshop personnel safety monitoring dashboard primarily publicizes potential safety issues detected through image recognition of video data collected by cameras. This allows factory safety officers to review and handle these issues. When a violation occurs, the system sends an alert to the safety officer's personal back-end interface. For false alarms, the safety officer can dismiss the anomaly alert through back-end management.

(3) Reagent dosage handling

The reagent dosage handling module allows technical operators to view the status of flotation processing equipment and the current status of reagent tanks and mixing tanks, and to increase or decrease the amount of reagent added. The system provides relevant auxiliary measures, issuing corresponding warnings in the case of excessive ore feeding or reagent addition. If a technical operator performs an incorrect operation, the system will not execute the command, issue a warning, and freeze the member's operation privileges for one day.

3.2. Performance requirements

The system will integrate control systems, data processing, and analysis tools into the industrial production environment to achieve intelligent, networked, and automated management and operations. Since the system needs to interact with users, user interface operations (such as clicks, queries, etc.) should respond within 1 second, and the generation time for complex charts and reports should not exceed 3 seconds. The system can adopt redundancy storage and backup strategies to ensure that data is not lost in the event of any single point of failure, guaranteeing 99.999% data reliability during data storage and transmission. During peak production periods, the system supports concurrent use by 2000 users, ensuring a data processing capacity of at least 2000 transactions per second. Additionally, the system employs a modular design to facilitate the integration and deployment of new modules.

3.3. System overview design

In the flotation process of iron concentrate, multiple factors affect the final grade of the minerals, making it a highly coupled process. Designing an intelligent reagent control system based on machine vision requires considering the strong coupling and internal mechanism complexity of multiple factors in the coal slime flotation process. Therefore, formulating a reasonable and effective technical route must adhere to design principles and meet the requirements of existing iron concentrate flotation processing technology.

3.3.1. Technical route of system design

The system designed in this paper is developed based on the beneficiation plant of Baotou Steel Co., Ltd. After two months of observation and learning in frontline production at the beneficiation plant, an in-depth analysis was conducted on the issues encountered during production. By integrating software design technology with mineral processing technology, the pain points and difficulties in the beneficiation process are addressed using relevant computer methods. Feasibility analysis, scheme research, and scheme demonstration are employed to explore the problems encountered in the project.

During the system design process, it is first necessary to review relevant literature and data on mineral flotation and collect relevant experimental data from the frontline processing site. The collected data, such as slurry concentration, mineral particle size, and reagent concentration, are processed. The processed data is used as the dataset for training, and the dataset is subjected to missing value handling and feature scaling. The dataset is divided into training and testing sets, and elastic net regression is used to train the dataset. The results of the trained model are then evaluated and tuned.

Simultaneously, photos of the factory are collected and taken, and objects such as vehicles appearing in the real-time status of the photos are marked. The YOLOv5 model is used to train the labeled data. After training, metrics such as Mean Average Precision (mAP) are used to evaluate the accuracy and performance of the model. After performance tuning, the model is applied to detect objects in new images using the YOLOv5 Python interface for object detection.

3.3.2. System architecture

The medication monitoring system utilizes the Django framework for the separation of front-end and back-end development. Django achieves this by creating different apps, writing data to these respective apps, and creating various view functions. This allows the Python back-end to provide JSON data responses to the front-end. Django modifies the traditional MVC framework by dividing the view into the View module and the Template module, with the two modules respectively responsible for dynamic logic processing and static page data. The Django framework uses a template engine to transmit data from the view to the client. It is necessary to specify the directory where the template files are stored in the project configuration file. In each app, the view's rendering functions based on Django need to be edited to bind the amount of data to be displayed. Corresponding template files need to be created in the template, and data transmitted from the view functions are received according to the corresponding template syntax of the template engine. The Model in the application handles data logic, encapsulating business data related to business logic and methods for processing data. Simply put, it is the interaction layer between the web framework and the database. Django's model layer adopts ORM (Object-Relational Mapping) technology, which converts tables in the database into abstract classes, making it convenient for view functions to call them.

The system adopts a B/S architecture and is deployed on Huawei Cloud servers using Nginx and Uwsgi. The Template module of the system employs HTML, CSS, and JavaScript in a static mode for front-end UI development. The view then receives requests from the user interface, invokes the appropriate processing logic, retrieves data from the model, and passes it to the template for rendering a response. This setup enables the system deployed on Huawei Cloud to interact with the Alibaba Cloud database. In terms of system security, Django's built-in security measures such as authentication, authorization, and Cross-Site Request Forgery (CSRF) protection are utilized to safeguard user production data and information. For factory safety monitoring and data processing, trained models are encapsulated within view functions to predict and process data from the production site, with the predicted results then uploaded to the front-end interface.

3.3.3. System function modules

The system enables the adjustment of the flow rate and status of each dosing port. Starting from the principles and processes of flotation, the system analyzes key influencing factors in flotation and detects some of these critical factors. It achieves real-time data collection and historical data storage of flotation process parameters. Operators can upload accurately tested data. Engineering technicians can compare computer-predicted values with uploaded data to optimize algorithms and improve mineral processing techniques. The system can present data from the database in the form of pie charts or linear graphs for flotation site, workshop safety, reagent dosage, and sales detection. Based on the data obtained from the system's dashboard, engineering technicians can adjust production processes according to relevant data indicators. The system function modules are shown in **Figure 1**.

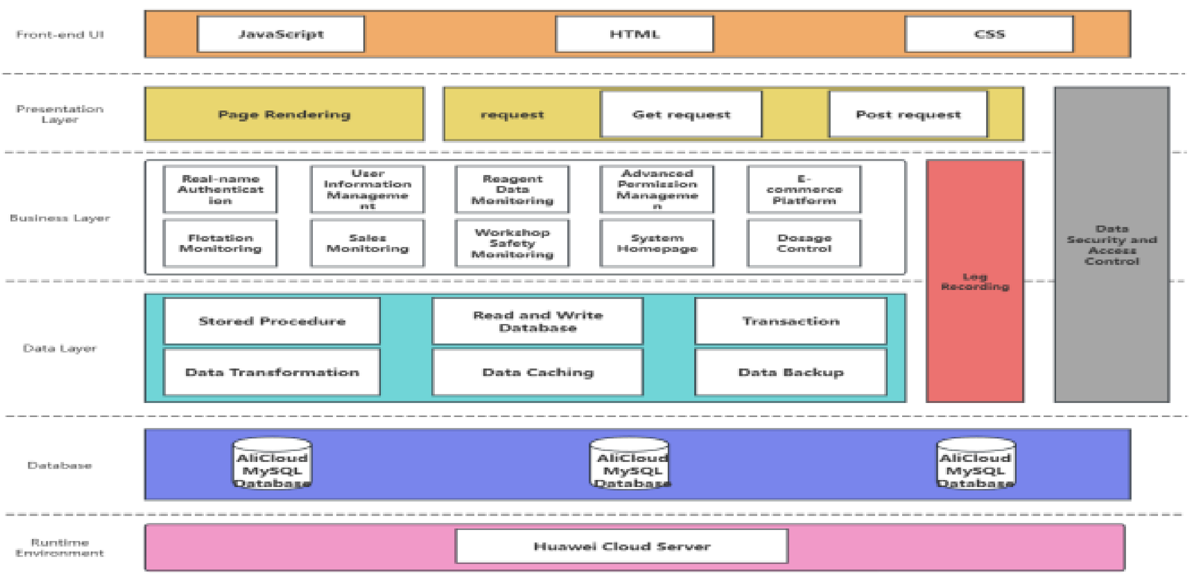

Figure 1. System architecture diagram.

3.4. Data preprocessing

3.4.1. Introduction to the dataset

In developing the prediction model for the flotation concentrate grade and the optimal reagent dosage, the dataset used for training is crucial in the early stages. However, the dataset required for the development of this system was not available on the public dataset platform of the Great Interconnection Company. The lack of a dataset has become a key issue in the development of this system. Therefore, due to the dataset's absence, this paper adopts a manual collection method to obtain a dataset suitable for training the predictable grade of the flotation concentrate and the optimal reagent dosage, including the relationship data of concentrate and tail iron, sulfur grade, and mineral yield.

(1) Flotation dataset

The dataset concerning the relationship between the iron and sulfur content in the tailings and the mineral yield (hereinafter referred to as the flotation dataset) was generously supported by the Inner Mongolia University of Science and Technology and the Key Laboratory of Multiple Utilization of Mineral Resources in Baiyunebo Mine, Inner Mongolia Autonomous Region. The flotation dataset is divided into three parts. The first part includes the state values during different mineral flotation periods, including the grades of iron and sulfur in the slurry, concentrate, and tailings. The second part includes the concentration of xanthate and the concentration of sodium hexafluorosilicate added during flotation. The third part includes the flotation concentration and the final yield. The total amount of the flotation dataset is 1000 entries, with 70% used as the training set and 30% used as the test set. The format is the commonly used .csv file in machine learning. CSV (Comma-Separated Values) files are lightweight text files that use plain text, with each line representing a data record and different attributes separated by commas.

(2) Safety warning dataset

In this system, safety warnings primarily involve two aspects: first, employees in the workshop must wear safety helmets to ensure personal safety during work; second, vehicle entry management within the factory premises is stringent, requiring all vehicles to be strictly monitored. Therefore, the safety warning dataset comprises four types: safety helmets, heads, people, and vehicles. The datasets for safety helmets, heads, and people are sourced from the publicly available dataset "Safety Helmet Detection" on Alibaba Tianchi, while the vehicle dataset is sourced from the "Car License Plate Detection" dataset on Alibaba Tianchi. The annotated dataset is in the standard YOLO format, with a total of 9570 images.

3.4.2. Data preprocessing

(1) Integration and cleaning of floating dataset

The flotation data in this study is sourced from the Key Laboratory of Multi-technology Utilization of Baiyun Obo Mine, Inner Mongolia University of Science and Technology. Initially, the data was stored in separate files according to different record dates. However, for machine learning purposes, the data needs to be integrated into a single dataset. This can be achieved using EXCEL to combine the individual files into a comprehensive data.csv file. The dataset also contains some missing items and outliers due to data collection issues. These anomalies can affect the feature extraction process in machine learning. In this study, the merged data.csv file is read using the read_csv function from the Pandas library in Python. Missing and anomalous values are replaced with the mean value of the corresponding column to mitigate their impact.

(2) Annotation of safety warning datasets

Due to issues such as incomplete annotation information, unclear division between training and testing sets, and inconsistent annotation formats in the acquired datasets, manual re-annotation was performed using LabelImg during the development of the safety warning model. LabelImg is a graphical image annotation tool written in Python and using Qt for its graphical interface. It supports the YOLO annotation format. The annotation process involves the following steps: first, defining the list of classes used in training in data/predefined_classes.txt; second, opening the directory and creating a "RectBox" to construct a rectangular box around the selected area; and finally, selecting the class name from the label list to complete the annotation.

(3) Image loading

In deep learning, image preprocessing is a crucial step that can directly affect the performance of the trained model. The preprocessing of the safety warning dataset includes normalization, denoising, and grayscale conversion. This paper utilizes the OpenCV library in Python, which provides many tools for image processing. The pre-divided safety warning dataset is loaded into the program and then loaded as a Numpy array called "image". According to the YOLO dataset, each image is scaled based on its corresponding category, the center position of the target object, and the length and width of the target object. Subsequently, the target object's area is cropped using array indexing. Each "image" array is normalized to a range between 0 and 1 by dividing by 255.

(4) Image grayscaling

Grayscaling the loaded images results in images that contain only luminance information, which can reduce storage space and computational complexity. Color images typically consist of three channels: red, green, and blue (RGB channels). Each channel corresponds to a specific color, but grayscale images have only one channel. Therefore, the pixel values of the three channels in a color image need to be converted to a single grayscale value. OpenCV uses a weighted average method for grayscaling, based on psychological experiments that determine the human eye's sensitivity to different colors. The weights for red, green, and blue are used to calculate the grayscale value through weighted averaging. The specific calculation formula is as follows:

$$Grayscale = 0.299Red + 0.578Green + 0.114Blue \tag{1}$$

(5) Image deionizing

Denoising can reduce the interference of noise in subsequent processing, improve the accuracy and stability of algorithms, and enhance the features within images, making subsequent feature extraction tasks more accurate and reliable. In this paper, the image denoising process employs the Gaussian Blur function. Gaussian Blur is a commonly used image blurring technique that smooths an image by applying a Gaussian filter, thereby reducing noise and fine details within the image. The Gaussian Blur utilizes the Gaussian function as a weighting function [11]. Due to the symmetry of the Gaussian function in the spatial domain, it effectively reduces high-frequency noise in the image. The weight calculation of the Gaussian filter is based on the distance of each pixel within the window, where pixels farther from the center have less influence on the output, while pixels closer to the center have a greater influence. Consequently, Gaussian Blur smooths the image and reduces noise.

4. Data preprocessing models

4.1. Yield prediction model based on neural network regression

(1) Multivariate regression performance

There are two commonly used models for traditional machine learning regression problems: the Linear Model and the Polynomial Model. These models perform well when the data exhibits linear relationships and there is no correlation between features. However, in the mineral flotation process, factors such as grinding particle size, aeration rate, stirring speed, slurry concentration, and pH value affect the process. The dataset encompasses numerous essential attributes and influencing parameters, which can lead to an increase in the polynomial degree and the number of terms in the regression model. This, in turn, affects the development efficiency and the quality of the model. The following is scatter plot 6.1 of the flotation dataset, generated using multivariate function fitting on the SPSSRO platform (an online data analysis platform). It is evident from the visualization that the fitting results are suboptimal due to the complexity of the data.

$$\hat{y} = b_0 + b_1 x + b_2 x^2 + \cdots + b_m x^m$$

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_1^2 + b_4 x_2^2 + b_5 x_1 x_2$$

(2) Introduction to neural network regression

Neural Network Regression (Quantile Regression Neural Network, QRNN), proposed by Taylor, is a non-parametric and non-linear regression algorithm that combines the advantages of both neural networks and regression [12]. See **Figure 2**.

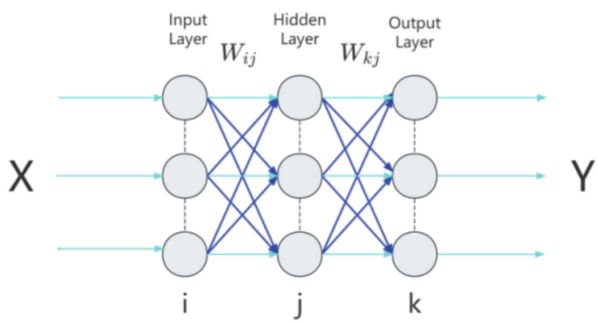

Figure 2. Neural network model diagram.

In a single-layer network, let's assume the input is (X), the output of this layer is (A), and the final output is (Y). Thus, in this single-layer network, this study has:

$$Y=A=\sigma(W^T X+b)$$

Assuming that ($Z=W^T X+b$) is a linear process, and the activation function (σ) is generally non-linear, the overall model is therefore a non-linear function. The parameters (w) and (b) that the model needs to learn can be collectively referred to as (θ). In the above equation, each quantity is generally a matrix. Assuming the shape of (X) is ((n, m)), where (n) represents the sample length and (m) represents the number of samples, the shape of (w) would be ((n, 1)), and (b), (Z), (A), and (Y) would be ((1, m)), representing the output values of (m) samples. For regression problems, the activation function (σ) commonly used is the ReLU (Rectified Linear Unit) function, defined as:

$$A=\sigma(Z)=\max(0,Z)$$

The accuracy of the neural network's predictions for a problem is measured by a loss function. For regression problems, the commonly used loss functions are Mean Squared Error (MSE) and Mean Absolute Error (MAE). MSE is suitable for data with a more concentrated distribution, so this paper uses the MSE function:

$$\mathrm{Loss} = \frac{1}{N}\sum_{i=1}^{N} (y_i - \widehat{y_i})^2$$

After computing (Y) through forward propagation, backpropagation is needed to compute the partial derivatives of the cost function (J) with respect to the parameters at each layer of the neural network, and use these derivatives to adjust the values of the network parameters. According to the Gradient Descent method, this study has the optimization function:

$$\mathrm{Optimizer}\ (\theta) = \theta - \alpha\frac{\partial J}{\partial \theta} = \theta - \alpha d\theta \text{ (}\alpha\text{is the learning rate)}$$

Using this formula, the parameter (θ) will change in the direction of the steepest descent of (J) during each backpropagation process. Thus, the forward and backward propagation process is essentially training the neural network. In this process, the model's parameters (θ) fit the sample distribution, which is referred to as learning.

(3) Implementation of yield forecasting model

Based on the completion of data preprocessing, a neural network model is constructed. This paper's neural network model is implemented using the PyTorch deep learning framework. In this model, there is one input layer, three hidden layers, and one output layer. The concentrations of the yellow medicine, collector sodium hexafluoride, original ore iron content, and flotation concentration are aggregated into a two-dimensional matrix and then converted into an input feature matrix, which serves as the parameters of the input layer. The output layer's results are then propagated forward through a series of linear transformations and activation functions into the subsequent three hidden layers. During this process, each neuron calculates the weighted input and applies an activation function to produce an output, which is then passed through the network. Upon reaching the output layer, the neurons of the last layer provide the predicted output. The MSE function is then used to calculate the loss function, which measures the difference from the true values. The network's backpropagation is performed based on the value of the loss function, while the contribution of each parameter in the model to the loss is calculated according to the chain rule. The gradient descent algorithm is then used to adjust the model parameters. Through multiple iterations, the model gradually converges and improves its accuracy.

(4) Evaluation of the yield prediction model's performance

The yield prediction model primarily addresses the influencing factors of mineral flotation and the yield of iron ore, with data presented in tabular form. This experiment evaluated the impact of flotation concentration, temperature, pH value, and particle size on the flotation process. First, scatter plots of the influencing factors and yield were drawn. Using the parameters obtained from the trained model, the model graph was plotted, and the accuracy of the resulting data reached 94.76%, as shown in **Figure 3**.

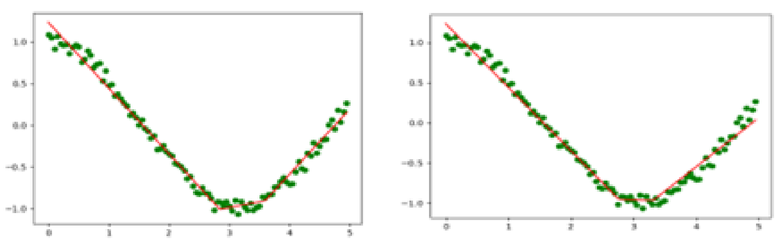

Figure 3. Model fitting effect diagram.

4.2. Factory safety monitoring model based on YOLOv5

4.2.1. Introduction to YOLOv5 model

YOLOv5 is an object detection algorithm in the realm of computer deep learning. It builds upon and optimizes the YOLO (You Only Look Once) series. As shown in Figure 8, YOLOv5 mainly comprises four components: Input, Backbone, Neck, and Prediction.

The primary task of the input component is to correct coordinates based on the width and height of all images in the dataset before each training session. It uses the k-means algorithm to cluster detection boxes in the training set to obtain initial anchors, and then applies a genetic algorithm to mutate these anchors to achieve the optimal anchor boxes. YOLOv5 also incorporates Mosaic data augmentation, which combines and stitches multiple images to produce new images, thus enhancing the effectiveness of the training set. See **Figure 4**.

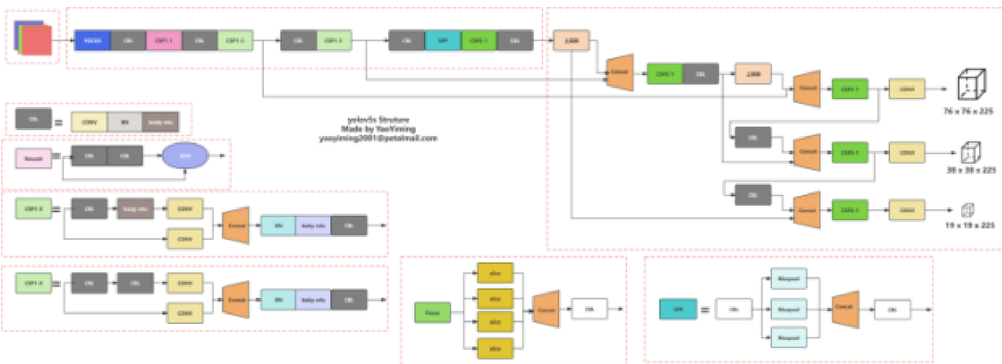

Figure 4.YOLOv5 network architecture.

The main function of the Backbone is to extract features and progressively reduce them. The Backbone is primarily composed of the Focus and CSP structures. The Focus structure slices the image, taking one value every pixel, thereby decomposing the entire image into four independent feature layers and concentrating the width and height information in the channel space. The original RGB three channels are thus transformed into 12 channels [13]. After applying convolution operations, sampled feature maps are obtained. The CSP structure divides the obtained feature map into two parts: one part undergoes convolution operations, while the other part is cross-connected with the convolution structure of the first part, enabling the model to capture more features. In object detection tasks, the Backbone utilizes CSPNet, which significantly enhances the learning capability of CNNs while also reducing computational cost.

The Neck structure of YOLOv5 aims to improve the network's feature fusion ability by converting feature maps of varying sizes into fixed-size feature vectors using the SPP pooling structure. Since the positions and sizes of objects in the original images are not fixed, YOLOv5 employs an FPN mechanism to add feature layers in the Backbone, generating feature maps with multi-scale information to improve the accuracy of object detection.

The Head is primarily used in the post-processing stage of object detection to filter the bounding boxes. During object detection, redundant candidate boxes and overlapping bounding boxes may be generated. YOLOv5 utilizes the Non-Maximum Suppression (NMS) algorithm to search for local maxima and suppress non-maximal elements, thereby selecting the optimal bounding box.

4.2.2. Implementation of factory safety monitoring model

YOLOv5 offers four different model structures: Yolov5s, Yolov5m, Yolov5l, and Yolov5x, with Yolov5s being the smallest model. In ascending order, Yolov5x is the largest model. Larger models offer better performance and stability, but they also require more time and computational resources for training. After comprehensive consideration, this paper adopts the Yolov5m model. Model configuration parameters are stored in a train.yaml file, with the number of classes (nc) set to 4, batch size (batch_size) set to 16, learning rate set to 0.001, number of epochs set to 200, and input image size (img_size) set to 416. The loss function weights are set as follows: loss: xy = 1.0, wh = 1.0, cls = 1.0, obj = 1.0, l1 = 0.1. After setting these parameters, the safety alert dataset is imported into the library to start training. Once training is completed, the trained model is evaluated using the validation set. The accuracy of the model is determined by calculating the difference between the predicted results and the actual annotations. These steps are iteratively repeated to improve the model's performance.

For safety alerts in factories, the model often receives frames from video surveillance. However, the YOLOv5 model processes images. In this paper, the Python OpenCV2 library is used, and the default camera device is opened using cv2.VideoCapture(0). Then, the cap.read method is continuously called to read the frames captured by the camera one by one, and each frame is passed to the input end of the YOLOv5 model.

5. Conclusion

5.1. Work summary

To address the long-standing issue of relying on manual control in flotation processing, which compromises plant safety, this study conducted an in-depth investigation at the Baotou Steel Group. It was found that in traditional mineral flotation processing, operators must manually adjust the reagent dosage and flotation cell levels. Manual operations suffer from a lack of accuracy and timeliness, making it difficult to meet the technical standards of the flotation process. To solve the problems of manual dosing accuracy and timeliness, this project collected images and flotation index data from the Baotou Steel Group's multi-technical resource utilization key laboratory in Inner Mongolia. Using a neural network propagation algorithm, the flotation index data were trained to predict yield.

Additionally, the chemical reagents used in the processing, such as cyanides, traditionally rely on human supervision, which can lead to safety hazards due to supervisory lapses, posing serious risks to production safety. To address the inefficiencies of human supervision and the high-risk nature of factory workers' jobs, this study utilized images from the processing site and the Alibaba Tianchi database. These images were annotated, denoised, and converted to grayscale, and then trained using the YOLOv5m model to analyze images transmitted from cameras. This enables monitoring of on-duty staff safety and factory site access. The machine learning-based mineral processing flotation reagent monitoring system implemented five functional modules: production indicators dashboard, workshop personnel safety monitoring dashboard, flotation reagent procurement platform, user access management, and flotation reagent dosage processing. This system achieved intelligent operation management for the mineral processing flotation plant.

The core advantages of the mineral processing flotation reagent monitoring system lie in its intuitive and precise data visualization, reduction in reagent consumption, and assurance of processing safety. The production index dashboard visually displays the optimal reagent dosage predicted based on industrial site data. Experimental results have proven the application of the new system, showing a 4.84% increase in concentrate yield and a reduction of 0.15 kg in reagent consumption per ton of iron concentrate ore.

Disclosure statement

The authors declare no conflict of interest.

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