Dynamic Prediction of Abnormal Condition for Multiple Fused Magnesium Melting Processes Based on Video Continual Learning

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Abstract

Process industry is the pillar industry of national economy, particularly, the process of producing magnesia by fused magnesia furnace system is a typical category of process industry. Due to the complex smelting mechanism and changing production factors, abnormal working conditions often occur in fused magnesia furnace. The semi-molten condition is the most typical and harmful abnormal condition. In this paper, an adaptive pretraining-inference-dynamic training-validation semantic segmentation method based on industrial video is proposed for dynamic prediction of semi-molten condition of multiple fused magnesium furnaces. The experimental results show that compared with the prediction model without adaptive learning, the prediction performance of the adaptive learning model in this paper for multiple fused magnesium melting processes is significantly improved.

Full Text

Preamble

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Zhang Zhe

Abstract– Process industry is the pillar industry of the national economy, and the production of magnesia through fused magnesia furnace systems represents a typical category within this sector. Due to complex smelting mechanisms and variable production factors, abnormal working conditions frequently occur in fused magnesia furnaces, with the semi-molten condition being the most typical and harmful among them. This paper proposes an adaptive pretraining-inference-dynamic training-validation semantic segmentation method based on industrial video for the dynamic prediction of semi-molten conditions across multiple fused magnesium furnaces. Experimental results demonstrate that compared with prediction models without adaptive learning, the adaptive learning model proposed in this paper achieves significantly improved prediction performance for multiple fused magnesium melting processes.

Index Terms– Semantic segmentation, Video Continual Learning, Abnormal Condition Prediction, Multiple Fused Magnesia furnaces.

1 INTRODUCTION

Process industry is the pillar industry of the national economy, and the production of magnesia through fused magnesia furnace systems represents a typical category within this sector. Due to complex smelting mechanisms and variable production factors, abnormal working conditions frequently occur in fused magnesia furnaces, particularly the semi-molten condition, which is the most typical and harmful abnormal state. If not processed in time, it can lead to molten leakage, low-grade magnesia products, and severe safety accidents. This paper proposes an adaptive semantic segmentation method based on industrial video for the dynamic prediction of semi-molten conditions across multiple fused magnesium furnaces.

We first introduce the research background of semi-molten condition prediction for fused magnesium furnaces and examine the current state of research on condition recognition and prediction, as well as adaptive deep learning both domestically and internationally. Based on video data from multiple fused magnesium furnaces, we carefully construct the training dataset. This paper designs an end-to-end convolutional neural network based on 3D U-Net and proposes an adaptive pretraining-inference-dynamic training-validation method for predicting semi-molten conditions in multi-furnace fused magnesium furnaces. The effectiveness of the proposed method is verified through industrial datasets. The main contributions of this paper are as follows:

We first investigate the production process mechanism and semi-molten condition characteristics of fused magnesium furnaces, identify the phenomenon of video feature migration across multiple furnaces, and review research on abnormal condition recognition and prediction based on process variables or computer vision, as well as the current state of adaptive deep learning. The specific problems addressed and main contributions of this paper are systematically summarized.

To address the challenge of quickly and effectively obtaining labeled data for multi-furnace working condition videos from fused magnesium furnaces, we propose an improved semi-automatic labeling method for semi-molten conditions. First, we select videos of smelting conditions from multiple furnaces and coarsely label the abnormal regions in each video frame based on spatio-temporal coordinate transfer methods. Subsequently, we optimize the spatio-temporal consistency of abnormal region labels using Weighted Median Filtering and Gaussian Filtering, creating a dataset for semi-molten condition prediction containing pixel-level labels of abnormal regions.

Considering various interferences present in industrial environments, this paper proposes a 3D U-Net convolutional neural network to train the semi-molten condition prediction model. To address problems of environmental light fluctuation and inherent furnace wall characteristics, the neural network preprocesses image sequences of each video frame through a temporal sequence consistency transformation module.

To tackle the problem of video feature migration in multi-furnace production processes, this paper proposes a dynamic prediction method based on adaptive deep learning. Grounded in the concept of end-edge-cloud collaborative learning, the method adaptively updates the cloud database using a sample balance screening mechanism. Multiple prediction models are adaptively switched through a multi-condition trigger mechanism based on validation accuracy, and an LSTM network estimates the pixel threshold for the semi-molten condition prediction model, thereby achieving adaptive learning of data characteristics from new furnace videos.

Through experiments, this paper investigates the influence of new buffer data volume on prediction results and verifies the effectiveness of the proposed LSTM-based threshold estimation method for improving prediction accuracy in the presence of video feature migration. Furthermore, experimental results demonstrate that compared with CRNN and 2D U-Net models, our adaptive dynamic learning model achieves the highest prediction accuracy and lowest missing rate for semi-molten condition prediction tasks based on open datasets and water mist-disturbed datasets collected from multi-furnace fused magnesium furnaces.

2.1 Abnormal Condition Prediction for Multiple FMFs

With the development of industrial artificial intelligence and industrial Internet technologies, data modeling, condition monitoring, fault diagnosis, and control optimization for complex controlled objects based on mechanism analysis and process variable big data-driven methods have gradually become research hotspots in process industry manufacturing.

The fused magnesium furnace (FMF) is typical major energy-consuming equipment in process industries. The FMF production system melts magnesite into fused magnesia through electrothermal reactions. Production factors are complex and variable, with numerous interference factors. As an important strategic material, fused magnesia exhibits characteristics of fire resistance, high-temperature resistance, corrosion resistance, and oxidation resistance, finding wide application in industrial, aerospace, and military fields. The semi-molten condition is the most frequent and serious abnormal phenomenon in the production process. When this condition occurs, ore cannot be melted in time, and carbon dioxide gas produced by the decomposition of magnesium carbonate compresses the high-temperature molten liquid, burning through the protective layer of the furnace wall and causing direct contact with the furnace wall. This results in furnace wall burn-through and molten liquid leakage, posing threats to inspection worker safety and reducing fused magnesia grade. This paper employs an end-to-end adaptive pretraining-inference-dynamic training-validation method to extract features from multi-furnace fused magnesium furnace working condition video data.

Scholars have studied diagnosis and prediction of semi-molten conditions in fused magnesium furnaces. Regarding image feature research, paper [1] quantified five characteristics of semi-molten condition images: flame area, average color of the entire image, average color of the flame area, total color of the flame brightness area, and flame brightness, using a robust random configuration network to identify semi-molten conditions.

Based on dynamic video as the primary model input, paper [2] proposed using a deep convolutional generative adversarial network to generate new samples, compensating for the shortage of original sample numbers. During training, the smelting video was first framed, and then a convolutional neural network [3] was applied to each frame to extract features of furnace flame, semi-molten furnace wall, sparks outside the furnace, and background areas, establishing a detection and classification model for electro-fused magnesium furnace smelting process images. However, this method did not design targeted solutions for environmental light fluctuation interference and high brightness at the magnesium furnace smelting site.

Considering the dynamic information from temporal and spatial dimensions of magnesium furnace smelting videos, paper [4] proposed a CRNN semi-molten condition diagnosis method based on deep learning of sequential dynamic images. This work identified differences between water mist interference and semi-molten conditions on the time axis, introduced hyperparameters representing the influence of flame and water mist movement speeds on images, and processed gray-level consistency of images. Sequential residual images were used as network input to eliminate environmental light and inherent white spots on the furnace. CNN and RNN networks were employed to extract spatial and temporal features from sequential images respectively. However, this structure separates the extraction of spatial and temporal features in video sequences without further considering the coupling relationship between temporal and spatial dimensions.

Paper [5] studied classification methods for semi-molten conditions by selecting two process variables: complementary magnesium furnace images and current data. Multivariate image analysis technology replaced human eyes for magnesium furnace flame feature extraction. A semi-supervised learning framework based on regularization was used for modeling, with cross-entropy optimizing the classifier objective function, significantly improving training speed compared with traditional optimization methods. This paper transformed the feature fusion problem of current and image into a semi-supervised learning problem, reducing the workload of image tag labeling compared with supervised methods [4], [5]. During production and operation of the fused magnesium furnace system, real-time video data is generated, but labeling each frame of video images requires substantial time, preventing real-time online prediction of semi-molten conditions.

Therefore, through adaptive deep learning methods such as transfer learning [6], relying on small amounts of labeled or even unlabeled video information obtained in real time, predicting semi-molten industrial conditions of magnesium furnaces holds important industrial application and promotion value.

In the visible light range collectible by video signal acquisition equipment, it is difficult for the human eye to accurately detect early semi-molten areas with unobvious characteristics in real time under harsh and complex production environments, making it challenging to predict semi-molten condition occurrence and provide early warnings. The goal is to achieve and exceed the effect of direct human observation.

2.2 Image Segmentation and Open Set Learning

The U-Net network [7] is developed from the FCN fully convolutional neural network [8]. The skip connection layer transmits high-resolution information directly from the encoding path to the decoding path of the same dimension through data concatenation operations, providing more refined features such as gradients for image segmentation. Simultaneously, low-resolution information from the encoding path after multiple downsampling is transmitted to the decoding path to provide semantic information of segmentation targets within the whole image context. Information of relevant dimensions can be visualized through deconvolution [9]. The U-Net network is commonly used in high dynamic range image reconstruction, end-to-end semantic segmentation, and other fields.

Deep learning has greatly improved image segmentation accuracy. Paper [10] successfully applied deep learning methods to image segmentation for the first time, replacing fully connected networks with convolutional networks and rolling out small feature maps from large feature layers through transposed convolution to output segmentation maps of the same size as the original image. DeepLab Atrous Convolution [11] expands the receptive field while keeping computation unchanged, enabling grasp of more global image information when the feature map is reduced by the same multiple. The PSPNet network [12] is a pyramid scene parsing network that proposes a module with hierarchical global priority containing different scale information between subregions. Context information and multi-scale fusion improve segmentation accuracy. Mask R-CNN [13] accomplishes target detection and semantic segmentation simultaneously. The U-Net network [7] retains numerous feature channels in the expansion path, allowing more information to flow into the restored segmented image, and overlays feature maps of the same size from the compression path and expansion path through skip connections to reduce image information lost during compression.

Transfer learning is an important means to solve the fundamental problem of difficult access to labeled data in machine learning. Domain adaptation is a type of isomorphic transfer learning [6], where domain consists of data features and feature distribution as the main learning subject. The source domain is a domain with existing knowledge and rich supervisory information, while the target domain is the domain to be learned, generally unsupervised or with limited supervisory information. In studying semi-molten condition prediction for fused magnesium furnaces, magnesium furnace video data information is generated in real time. However, images of magnesium furnace working conditions obtained frame-by-frame have no labels, and the prediction network cannot know whether semi-molten conditions occur. Therefore, it is necessary to automatically label images through manual annotation or automatic working condition labeling methods based on weighted median filtering [4], or to design semi-molten condition classifiers based on deep neural networks [5], which introduces certain hysteresis in production prediction.

Unsupervised domain adaptation [14] does not require any labeled data in the target domain but needs large amounts of target domain data to adapt to data distribution without any semantic information. Semi-supervised domain adaptation requires only a small amount of tagged data in the target domain to achieve performance exceeding UDA [15]. In practical applications, small amounts of tagged data can be obtained in new fields, making this method more suitable for practical applications.

2.3 Dynamic Continuous Learning of Industrial Big Data

Dynamic open environments often exhibit characteristics of distribution deviation, category increase, attribute change, and target diversity [16]. Decision problems in dynamic open environments often demonstrate dynamic uncertainty [17], which weakens the robustness of artificial intelligence technology. When deploying artificial intelligence systems in high-risk tasks, we should study how to improve model robustness from both model and data levels [18]. To cope with unknown risks in open environments, we study feature distribution deviation of industrial video data caused by production environment changes.

The essence of semi-molten condition prediction for fused magnesium furnaces is image segmentation, which realizes recognition and prediction of semi-molten areas on furnace walls at the pixel level. Image segmentation refers to the technology and process of dividing an image into several regions with unique properties and extracting objects of interest. From a mathematical perspective, image segmentation is the process of dividing a digital image into disjoint regions. Its essence is to classify each pixel into categories or different independent individuals and extract a region or feature of concern to exclude redundant image information, which helps reduce computation for subsequent operations.

For image processing tasks, the accuracy of deep learning networks trained from scratch is not necessarily high. Based on existing training models built upon large amounts of training data, modifying model parameters can achieve better results. This is a pretrain–fine-tune strategy [19], where fine-tuning refers to applying the pretrained model to the target task dataset and adapting parameters to the target task data.

This paper studies adaptive deep learning methods for the semi-molten condition prediction model of fused magnesium furnaces. The prediction object of the model can be converted from closed set to open set. Based on the incremental learning idea of focal loss function [20], a prediction model based on historical video data is obtained through pretraining. The parameters of convolutional and fully connected layers are modified according to new video data through fine-tuning methods, and new model parameters are constrained by the loss function, ensuring the adaptive learning model remains effective for predicting semi-molten conditions in historical data while improving model generalization capability.

Simultaneously, according to the accuracy and loss values of prediction model performance, a model updating trigger mechanism is designed. The accuracy and loss function of semi-molten conditions are compared across validation sets of incremental training models, historical models, and pretraining models. The optimal model is automatically determined and saved, replacing the historical prediction model, which improves prediction accuracy for semi-molten conditions in new video data buffers.

3 Video Dataset Based on Multiple Fused Magnesia Furnaces

The dataset includes original images and labels for each video frame. The data labels reflect whether semi-molten conditions occur in each furnace video, the timing of semi-molten conditions, and the pixel-level regions. Only through accurate label production can models with high prediction accuracy be trained. Therefore, before designing the adaptive deep learning network for semi-molten conditions of fused magnesium furnaces, the working condition videos of fused magnesium furnaces should be analyzed, and video clips containing both semi-molten and normal conditions with appropriate duration should be extracted from multiple furnaces to produce a dataset containing working condition images and their pixel-level labels.

The working condition videos are .MTS format files collected by Sony video acquisition equipment, which need to be converted into AVI format files. Subsequently, labels are created using Matlab and saved as data files in .MAT or .HDF5 format. The preprocessed images of each video frame are used as network input, and the working condition labels created through weighted median filtering and other methods serve as the expected model output. The three-dimensional U-Net neural network based on temporal consistency transformation is then trained to obtain the semi-molten working condition prediction model.

In this paper, MAT neural network training datasets are produced based on production condition videos from two fused magnesium furnaces. This method can be applied to multi-furnace video dataset production. First, this paper selects three videos with proportional balance between semi-molten and normal conditions and analyzes the temporal and spatial distribution of semi-molten areas.

Regarding semi-molten area label production, we first use the spatio-temporal coordinate transfer method to coarsely label semi-molten areas, then apply weighted median filtering to the video image sequence to optimize the coarse semi-molten labels. The label transfer method of adjacent frames solves the problem of individual labels being abnormally zero due to small semi-molten areas. Furthermore, based on the label transfer method, spatio-temporal consistency of semi-molten labels is optimized through Gaussian filtering, producing semi-molten area labels with smooth edges and high accuracy. The more accurate the semi-molten area labels, the more precise the position of semi-molten areas predicted by the model, providing a reliable dataset for training the semi-molten prediction model in this paper.

4 Adaptive Dynamic Prediction Method for Abnormal Conditions

The smelting system of fused magnesium furnaces is a complex practical industrial production system. Currently, some scholars have selected process variables such as magnesium furnace working condition images [2], [4], [5], [21], graphite electrode current, current fluctuation rate [22], average gray variance of melting zone, and molten pool liquid level rise rate [23] to study magnesium furnace working conditions. Among these, graphite electrode current fluctuates frequently with changes in ore particle shape, composition, and voltage, exhibiting strong time-varying characteristics that make stable and accurate long-term inference difficult. Variables such as molten pool page rising speed are difficult to obtain and have insufficient data volume [24], presenting challenges in establishing coupling relationships between electrode current and magnesium furnace images across temporal and spatial dimensions.

To enhance the generalization ability of the semi-molten condition prediction model, this paper adopts the idea of incremental learning. Incremental learning does not require storing large amounts of historical video data, reducing storage space occupation while making full use of training results based on historical data, which significantly reduces subsequent training time. The strategy of pretraining-dynamic learning-dynamic inference-model validation is adopted.

With continuous updating of video data, adaptive learning of all convolutional and fully connected layers in the three-dimensional U-Net network is realized. An adaptive updating strategy for training data based on sample balance screening mechanism is proposed, and an adaptive correction strategy for multi-prediction models based on trigger mechanism is designed. Furthermore, a threshold estimation method for semi-molten condition prediction models based on long short-term memory networks is proposed, realizing adaptive deep learning for semi-molten condition prediction models of multi-furnace magnesium furnaces.

Combined with the parameters of magnesium furnace video sequences introduced in this paper, the model training objective function is as follows:

$$L(Y_k, \hat{Y}_k^m) = -[\alpha \cdot Y_k (1 - \hat{Y}_k^m)^\gamma \log(\hat{Y}_k^m) + (1-\alpha) \cdot (1 - Y_k)(\hat{Y}_k^m)^\gamma \log(1 - \hat{Y}_k^m)].$$

Regarding adaptive model correction, a validation set updating method based on fixed buffer updating is proposed. After each new buffer dataset is added, a validation set updating mechanism is triggered, selecting a fixed number of tuples from the first tuple of the training set along the time dimension, which is called fixed buffer updating validation set. The Adaptive Correction Strategy for Multiple Forecasting Models Based on Triggering Mechanism is shown in the following formula, where index L represents the loss function value:

$$M_{pre}, L_{pre} M_{his}, L_{his} M_{train}$$

However, the validation set determined by this method is too far from the new buffer data in the time dimension, and data characteristics of the validation set and new buffer data may differ significantly. Therefore, this paper further proposes a buffer-by-buffer dynamic updating method for the validation set.

The specific steps are as follows: After adding a new buffer to the training set, starting from the last tuple of the training set before the new buffer, historical data are traced along the time dimension to obtain equal numbers of data source groups with semi-molten condition labels and normal condition labels respectively. The validation set is updated buffer by buffer through splicing and sequence disruption. In this paper, validation set data is enhanced to increase the number of images in the validation set.

5 Experiment and Analysis

Based on experience, the transition from normal condition to semi-molten condition in fused magnesium furnace operation typically takes about 20 to 50 seconds. First, based on the pretraining-inference-dynamic training-validation idea, adaptive learning is performed for each new buffer of image sequences. After learning, the semi-molten condition of the next new buffer is predicted. Based on this idea, 300 image-label tuples with new buffer numbers are selected for experimental validation. The model is evaluated primarily from the actual prediction accuracy and the maximum potential prediction accuracy of the model.

Furthermore, this paper expands the adaptive learning dataset and further increases the number of tuples in each buffer. Multiple sets of experiments are conducted with different tuple numbers. The prediction metrics—accuracy, missing rate, and error rate—of the incremental model and the pre-training model trained in this paper are compared under different conditions such as fixed test threshold, dynamic test threshold, and optimal test threshold, respectively, verifying the effectiveness of the adaptive deep learning method for fused magnesium furnace proposed in this paper.

Threshold-based classification is a common method. The essence of the proposed test threshold is a binary classification threshold with a value range of -0.01 to 0.99. When the semi-molten condition prediction model predicts the working condition of the new buffer image sequence, this paper compares the pixels of pixel-level semi-molten region segmentation results corresponding to each frame image sequence predicted by the model (value range 0.00 to 1.00) with the test threshold. If the pixel value is less than the test threshold, the pixel value is set to 0, and we consider that no semi-molten condition exists at that pixel point, and vice versa.

Overall, the prediction capability of the semi-molten condition prediction model and the test threshold value determine model reasonableness. Previous research predicted large-scale data from the same furnace, assuming these data labels were known, so the optimal threshold for large-scale data from the same furnace was used as the test threshold. However, the key of this study is to predict small buffer data from different furnaces in buffers.

Combined with industrial practice, labels for small buffer data of each buffer are unknown, so the test threshold is also unknown. Therefore, we make reasonable assumptions combined with actual production processes and propose methods based on data patterns and LSTM long short-term memory networks to predict test thresholds for small and large new buffer data. Experimental results demonstrate the effectiveness of both methods.

This paper experimentally studies the adaptive deep learning method for underburning condition prediction of fused magnesium furnace. Experimental results show that the proposed method can greatly improve prediction accuracy for new furnace videos.

Table 1 Prediction results by various models proposed in this paper

Forecast indicators	Inference threshold estimator	Gro size 600	Gro size 2400
ACC Adaptive Data Rule or LSTM	91.23%	87.20%	

Forecast indicators	Inference threshold estimator	Gro size 600	Gro size 2400
ACC Adaptive Historical Threshold	88.67%	76.64%	
ACC Pretrain Fixed Threshold	72.11%	71.24%	
ACC Adaptive Upper Previous Optimal Thre	95.44%	92.67%	
MissR Adaptive Data Rule or LSTM	0.98%	7.66%	
MissR Adaptive Historical Threshold	2.75%	10.68%	
MissR Pretrain Fixed Threshold	21.46%	21.98%	
MissR Adaptive Upper Previous Optimal Thre	2.51%	5.38%	
ErrorR Adaptive Data Rule or LSTM	7.79%	5.14%	
ErrorR Adaptive Historical Threshold	8.58%	6.43%	
ErrorR Pretrain Fixed Threshold	2.05%	12.68%	
ErrorR Adaptive Upper Previous Optimal Thre	6.87%	1.95%	

According to Table 1, the dynamic prediction model of abnormal conditions proposed in this paper can improve prediction capability for semi-molten conditions in new videos with changed data characteristics through adaptive deep learning. Taking 600 image sequence-tag pairs with new buffer data (group size = 600) as an example, when using a fixed test threshold (i.e., the optimal test threshold obtained by the pretrain model for all data from new furnaces), the pretrain model based on historical furnace video data training achieves 72.11% accuracy, 21.46% missing rate, and 6.43% error rate for predicting semi-molten conditions in new furnaces. In contrast, the adaptive deep learning method improves accuracy to 91.23%, reduces missing rate to 0.98%, and achieves 7.79% false reporting rate. It should be noted that error rate and missing rate are negatively correlated and both relate to the test threshold, so these two indicators should be studied together. Experimental results verify the effectiveness of the proposed adaptive deep learning method for semi-molten conditions based on dynamic threshold.

Simultaneously, we find that if new buffer data is small, adaptive learning time and computational amount will increase significantly. There may also be cases where data characteristic changes are minor, making adaptive learning advantages less obvious, which deviates from the key content of this paper.

The prediction model and pre-training model results are compared and analyzed when new buffer data takes different values. It is verified that compared with the pre-training model, the adaptive deep learning method in this paper can greatly improve prediction accuracy and reduce missing rate and error rate.

Since semi-molten condition prediction is essentially a binary classification problem, prediction results relate to the test threshold. Therefore, under the premise of ensuring prediction accuracy meets requirements, this paper proposes two methods to predict the semi-molten ratio of new buffer data based on data patterns and LSTM respectively, determining the test threshold based on the relationship between semi-molten ratio and optimal test threshold.

Table 2 Prediction results of abnormal conditions compared with other models

Model	U-net	Proposed
ACC	72.38%	86.00%
MissR	21.32%	10.48%
ErrorR	6.30%	3.52%

As shown in Table 2, compared with the CRNN prediction model and the 2D U-Net prediction model, the adaptive learning prediction model in this paper achieves the highest prediction accuracy, verifying that the adaptive deep learning method can effectively learn new data characteristics. Moreover, the missing rate of our model is the lowest, confirming that the adaptive learning method can accurately predict semi-molten conditions and demonstrates good prediction capability for semi-molten conditions with small areas, low brightness, and difficulty in identification by human eyes. Additionally, we note that the proposed model may predict some normal conditions as semi-molten conditions. Since the purpose of this study is to predict all semi-molten conditions as far as possible, it is acceptable for the missing rate to be higher within a certain range, which may be due to inaccurate labels or the model' s ability to identify semi-molten characteristics difficult to observe with the naked eye. According to experimental results, compared with the CRNN prediction model and the two-dimensional U-Net prediction model, the adaptive deep learning method proposed in this paper demonstrates stronger prediction capability.

6 Conclusion

This paper proposes an adaptive deep learning method for multi-furnace semi-molten conditions to address the problem of changing video data characteristics across multiple furnaces. Experimental results show that compared with prediction models without adaptive learning, the adaptive learning model proposed in this paper significantly improves prediction accuracy for new furnace semi-molten conditions and substantially reduces prediction missing rate and error rate. Moreover, the adaptive learning model demonstrates high prediction capability for small-area and low-brightness semi-molten conditions that are difficult for human eyes to detect.

First, this paper investigates the research background of semi-molten condition prediction for fused magnesium furnaces as major energy-consuming equipment and reviews the current state of condition identification and prediction research both domestically and internationally, as well as the research status of adaptive deep learning.

Second, we select video data of multi-furnace semi-molten conditions from fused magnesium furnaces. We implement acquisition and coordinate calibration of multi-furnace semi-molten areas. Labels are optimized through weighted median filtering and Gaussian filtering, providing a dataset containing pixel-level labels of semi-molten areas for model training.

Furthermore, we construct a three-dimensional U-Net convolutional neural network containing a temporal consistency transformation module. Through incremental learning of other furnace video data by the pretraining model and adaptive updating mechanism based on trigger mechanism, we propose an adaptive deep learning method for semi-molten conditions of fused magnesium furnaces. Based on this method, experimental research is conducted, and test thresholds for new buffer video data are predicted based on data patterns and LSTM long short-term memory networks.

In this paper, multiple prediction models are designed and continuously improved. An adaptive deep learning model based on three-dimensional U-Net convolutional neural networks and a test threshold prediction method based on mathematical laws and LSTM long short-term memory networks are obtained. These adaptive models and test threshold prediction methods are collectively called the adaptive prediction method.

Further experimental results show that compared with CRNN and two-dimensional U-Net convolutional models, the adaptive deep learning model trained in this paper achieves the highest prediction accuracy and lowest missing rate. These experimental results prove the effectiveness of the proposed adaptive deep learning method.

Regarding future work prospects, this paper proposes an end-cloud collaborative reasoning framework corresponding to the adaptive learning method. In the future, the problem of weak supervision training can be solved through weak supervision domain adaptive methods when real-time working condition data of fused magnesium furnaces is acquired without labels.

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

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