Deep Fusion Feature Extraction and Classification of Pellet Phase

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ABSTRACT

Pellet quality including chemical composition, physical properties and metallurgical performance of three parts, its quality and mineral composition, properties and structure of the pellets has the close relation, studies show that the mineralogical micro structure and distribution of pellets had significant effects on the metallurgical properties, so the analysis and determination of pellets of mineral composition and micro structure is very important to improve the quality of pellets. Paper to pellets micro mineral as the research object, mainly studies the CNN and PCA two kinds of image processing algorithm, in the heart of the traditional model of CNN structure characteristics obtained by convolution PCA dimension reduction at a time, will be the main features of PCA to extract into the depth of the CNN learning, realize the mineral phase of shallow and deep information of the image to do effective fusion, in a larger extent, reflects the mineralogical characteristics, thus more intuitive response metallurgical properties. The location and alkalinity of the ore phase were identified by the extracted deep fusion feature, and the results were compared with those of the traditional CNN algorithm. It was found that the accuracy of location and alkalinity recognition of PCA and CNN coupling algorithm was 93.82% and 91.26%, respectively, which were higher than the accuracy of traditional CNN algorithm 92.73% and 88.93%, which verified the accuracy of PCA and CNN coupling model and its applicability in mineral phase recognition.

INDEX TERMS

CNN, feature fusion, PCA.

I. INTRODUCTION

Pellets are the main materials for blast furnace iron making, its quality directly affects the technical and economic indexes of blast furnace smelting. The quality control of pellet is a very complex process, including three parts: chemical composition, physical properties and metallurgical properties. For a long time, researchers at inland and abroad have always focused on the control of the expansion rate and reduction rate of pellets, improved the metallurgical properties of pellet and the production efficiency of blast furnace. In recent years, relevant research shows that the ore phase micro structure and distribution of pellets have a significant effect on their metallurgical properties [1]–[4], Therefore, it is very important to analyze and measure the mineral composition and micro structure of pellets to improve the quality of pellets.

More and more scholars pay attention to the study of mineralogical phase based on pellets. Wang Zunzhi (1989) studied the mineral phase structure characteristics of various ordinary pellets from the perspective of micro structure, combined the micro structure of pellets with metallurgical properties and came up with a new process for improving the reducibility of pellets [5]. Chen Yaoming, Chen Rui (2011) systematically introduces the basic theory of the micro structure of the agglomerate and the technology and method of ore phase identification, and summarized the micro structural characteristics of agglomerates and the crystallization law of minerals [6]. Luo Guoping, Zhao Bin, Liu Jingquan experimental studied on the ore phase structure of MgO pellets after reduction, concluded that the porosity of pellet is increased, improved the metallurgical properties of pellet, improved...
smelting strength, and reduced the Production plan of coke ratio [7]. Ding Mingming, Li Juan, Kong Fanbei etc(2018) used mathematical method to extract texture features of pellet micro mineral phase, and analyzed the characteristic parameters of ore phase with different alkalinity, so as to realize the discrimination of alkalinity and position of ore phase [8].

In conclusion, the research on the ore phase of pellets is still in the experimental research and analysis stage, and the research methods mainly adopt the traditional image processing algorithm and machine learning theory. Although with the rapid development of computer digital image processing technology, metallurgical workers began to introduce this technology into practical production [9]–[11]. But the application of deep learning model to the study of pellet ore phase is very few, convolutional neural network (CNN), as a new thing, has been applied in many fields, and got a great results.
The application of CNN model to the research of pellet ore phase will more effectively mine the depth characteristics of ore phase, help to achieve the goal of intelligent prediction of pellet quality, and promote the development of China’s iron and steel industry to the direction of intelligent industry.

II. MATERIAL SOURCES
The ore phase picture of pellet is measured by the Leica research microscope, 2000 groups of pellet samples with alkalinity of 0.6, 0.8, 1.0 and 1.2 were sliced and ground. The ore phases of the central part, 1 / 4 part and the edge part of the pellet were obtained under Leica research microscope, forming a labeled sample set as shown in Figure 1.

III. RESEARCH METHODS
A. FEATURE EXTRACTION METHOD OF DEEP FUSION OF MINERAL PHASE BASED ON CNN
CNN model is a kind of biophysical model, which imitates the nervous system of animal vision system, and is designed by using the idea of Receptive field that pictures have high invariance under the conditions of translation, zooming and tilting. It mainly deals with the recognition of two-dimensional images [12]–[15]. CNN’s feature extraction process is a process of mapping from shallow features to deep features. Shallow features are mainly represented by image texture, edge, level information and location information, with high resolution, while deep features are more abstract and complex semantic information. Each convolution process of CNN will get different characteristic information, and the convolution layer shows more spatial information than the full connection layer. CNN will filter the convoluted features layer by layer, and filter out some features through the pooling layer. In this process, it is inevitable that some features that affect the recognition results will be filtered out, reducing the performance of the model [16].

Therefore, the key to improve the deep learning model is how to effectively integrate the shallow features with the deep features, so as to improve the accuracy of the image recognition task. The production process of pellet is complex, involving many physical and chemical changes. The microstructure of pellet ore phase is the embodiment of pellet metallurgical performance. Its image is rich in texture, edge, level and position information, as well as complex semantic information. The effective fusion of shallow information and deep information of ore phase image can reflect the characteristics of ore phase to a greater extent more intuitive reactive metallurgical properties.

Principal component analysis (PCA), as a commonly used data simplification analysis method, reduces the redundancy and low correlation of the feature vector after dimension reduction, which reflects the nature of the feature to some extent, and is not easy to fall into over fitting when making classification prediction in the future, and is widely used in the field of digital image processing, and has achieved good results in image feature extraction [17], [18]. Therefore, this paper establishes the coupling algorithm of PCA and CNN as shown in Figure 2. In the traditional CNN model structure, PCA dimension reduction is carried out for the features obtained by each convolution, and PCA main feature extraction is integrated into CNN deep learning, which can realize the multi-layer feature fusion of shallow information features and deep features.

At present, according to the sequence of fusion and prediction, multi-layer fusion can be divided into early fusion and late fusion. Early fusion refers to the fusion of multi-layer features, and then training the classifier on the fused features. There are two basic methods of early fusion: add by points and concatenate by vectors. Late fusion is to improve the performance of model detection by combining the detection results of different layers, that is to say, segment detection is carried out on the segment fusion layer, and finally multiple detection results are fused. The representative research idea is pyramid fusion method.

In this paper, image feature fusion mainly has the following two purposes:
1) Avoid data missing in the process of image feature detection and judgment;
2) Improve the ability of image detection, classification, understanding and recognition.

In the coupling algorithm of PCA and CNN, the multi-layer image fusion method is early fusion, that is to say, the feature after convolution operation of each layer and the feature after dimension reduction of PCA are added and fused point by point, and finally output to the full connection layer, and then the model recognition results are detected uniformly, so as to enhance the performance of the whole model to the image.

B. CALCULATION METHOD OF COUPLING MODEL BETWEEN PCA AND CNN
Applying the coupling algorithm of PCA and CNN to the feature extraction of pellet ore facies, Establish a PCA and CNN coupling model based on mineral identification, combining image enhancement, Gaussian filtering, image segmentation and PCA dimensionality reduction with the original image to establish a data sample set as a model input. The main frame of the model uses the classic AlexNet network. The structural details and parameters of each layer of the AlexNet network are shown in Table 1.

The number of parameters of each layer is calculated by the product of the size of the convolution kernel and the number of convolution kernels plus the number of offsets, that is, the number of convolution kernels. In the fully connected layer, 4096 neurons are divided into two groups, and the pooling results of the previous layer are fully linked. The output layer outputs 1000 category labels, whose size can be adjusted according to the actual problem. In the problem of identifying the alkalinity of pellets, the number of category labels is 4, and in the problem of identifying the location of mineral phases, the number of category labels is 3.

The coupling model of PCA and CNN based on mineralogy recognition is integrated into the PCA dimensionality...
The main framework of the model uses the classic Alexnet network. The PCA and CNN coupling model based on the mineral phase recognition is integrated into the PCA dimensionality reduction process after each convolution of the feature image obtained by Alexnet. The multi-layer feature fusion of shallow information features and deep information features is realized, and the final fused feature information reduction process after each feature image obtained by AlexNet convolution to realize the multi-layer feature fusion of shallow information features and deep information features. The final fused feature information is used as the detection standard to identify the part of the mineral phase and the alkalinity. The model structure is shown in Figure 3.
FIGURE 3. The flowchart of identification and classification of pellet phase feature based on PCA and CNN coupling model.

is transferred into the full connection layer as the detection standard. The specific calculation steps are as follows:

Step 1: The ore phase in the center, 1/4 and edge of the pellet ore samples with alkalinity of 0.6, 0.8, 1.0 and 1.2 respectively. The processed ore phase, 20% as the verification set, and 20% as the test set;

Step 2: Convolution layer process: PCA dimension reduction → convolution → Relu → pooling → normalization → feature fusion. 96 convolution kernels of size are used, and the Relu function is selected as the activation function. The size of pooling operation window is $3 \times 3$, and the maximum value of step 2 is pooled. Finally, the normalized result and PCA are fused to extract the first fusion feature as the input of the second convolution. The number of parameters of the layer is 334944;

Step 3: Convolution layer process: PCA dimension reduction → convolution → Relu → pooling → normalization → feature fusion. Convolution kernel size is $3 \times 3$, function activation, pooling and normalization methods are the same layer, the number of parameters in this layer is 307456;

Step 4: Convolution layer process: PCA dimension reduction → convolution → Relu → pooling → normalization → feature fusion. The convolution kernel size is $3 \times 3$, function activation, pooling and normalization methods are in the same layer, and the number of parameters in this layer is 885120;

Step 5: Convolution layer process: PCA dimension reduction → convolution → Relu → pooling → normalization → feature fusion. The convolution kernel size is $3 \times 3$, function activation, pooling and normalization methods are in the same layer, and the number of parameters in this layer is 663936;

Step 6: Convolution layer process: PCA dimension reduction → convolution → Relu → pooling → normalization → feature fusion. The convolution kernel size is $3 \times 3$, function activation, pooling and normalization methods are in the same layer, and the number of parameters in this layer is 442624;

Step 7: Full connection layer process: full connection → Relu → Dropout. The network consists of two full connection layers. The input of the first full connection layer is multi-layer fused ore phase features. The layer has 37752832 parameters. The second full connection layer is connected with the output layer. For the model of ore phase location identification, the parameters of the layer are 12291. For the model of pellet ore alkalinity identification, the parameters of the layer are 16388;

Step 8: Output ore phase position or pellet alkalinity identification result of output layer;

Step 9: Input the validation sample set to evaluate the coupling model capability and further adjust the network parameters. The network selects the cross entropy cost.
function as the loss function to evaluate the model identification results. The change of the loss function value of the validation set and the training set in the training process is shown in Figure 34:

Step 10: input the test sample into the coupling model to verify the recognition accuracy of ore phase position and pellet alkalinity.

The number of parameters in each layer is calculated by the product of convolution kernel size and convolution kernel number plus offset number, that is, the number of convolution kernels. 4096 neurons are divided into two groups in the full connection layer, and the pooling results of the upper layer are fully linked. 1000 category labels are output in the output layer. The size can be adjusted according to the actual
problems. The basicity of the pellet phase can be identified. In other problems, the number of category labels is 4, and in ore phase location recognition, the number of category labels is 3.

IV. RESULT ANALYSIS
A. FEATURE ANALYSIS OF DEEP FUSION OF ORE PHASE
Figure 4-6 shows the feature extraction process of a certain ore phase sample with alkalinity of 0.6 in the center, 1/4 and edge under the framework of Alexnet.

By observing the center part, 1/4 part and edge part of the feature extraction image, it can be found that with the deepening of the model depth, the pixel of the image is lower and lower, but the main features are more and more obvious.

B. ACCURACY ANALYSIS OF ORE PHASE CLASSIFICATION
The reprocessing sample image is used as the input sample set to train the network in advance. The initial network learning rate and weight attenuation parameters are set to 0.1 and 0.0001 respectively. In the process of training, when the increment of loss function is more than 25%, the learning rate will be reduced by 50%, and the network with the best loss will be reloaded. Then, the position and alkalinity of pellets will be determined by the test samples according to the main features of ore phase extracted from the coupling model. It can be seen from Figure 7 that the coupling model performs well in both the test sample set and the verification sample set. When the number of iterations exceeds 600, the training loss is reduced to a satisfactory result and the model accuracy is high.

Finally, the training results of PCA and CNN coupling algorithm are tested with the test sample set, and compared with the results of traditional CNN model. The comparison results are shown in Table 2. It is found that the accuracy of PCA and CNN coupling algorithm is 93.82% and 91.26% respectively, which are higher than the accuracy of traditional CNN algorithm 92.73% and 88.93%.

Figure 8 shows the comparison results of the training loss function values in the process of identifying the mineral phase position of the test sample set by the two algorithms. Abscissa represents the number of iterations. With the increase of the number of iterations, the network loss value is declining. When the number of iterations exceeds 400, the loss value of
### TABLE 2. The recognition accuracy of the two algorithms.

| Algorithm   | Position recognition accuracy | Accuracy of alkalinity identification |
|-------------|-------------------------------|---------------------------------------|
| CNN         | 92.73%                        | 88.93%                                |
| CNN+PCA     | 93.82%                        | 91.26%                                |

![FIGURE 8. Training loss on test set.](image1)

![FIGURE 9. Accuracy of position recognition on test set.](image2)

The two algorithms tend to be stable. However, from Figure 7, it can be seen that the loss degree of PCA CNN coupling algorithm is significantly lower than that of traditional CNN algorithm, and the decline speed of the loss value is also higher than that of traditional CNN algorithm.

Figure 9 shows the comparison results of the accuracy of the two algorithms in the process of mineral phase location recognition of the test sample set. As can be seen from figure 8, when the number of network iterations is more than 400, the accuracy of the two algorithms tends to be stable, and the accuracy of CNN and PCA coupling algorithm is relatively more stable, maintaining about 94%. This shows that the coupling algorithm of CNN and PCA not only improves the recognition accuracy of traditional CNN algorithm, but also correspondingly improves the calculation speed of the model. Applying the coupling algorithm of CNN and PCA to the identification of pellet phase has a good effect and satisfactory accuracy, which has a certain theoretical guidance significance for pellet production and quality control.

### V. CONCLUSION

1. Pellet ore phase image not only has rich texture, edge, level and location information, but also has complex semantic information. The effective fusion of shallow information and deep information of ore phase image can reflect the ore phase characteristics to a greater extent, so as to have more intuitive reactive metallurgy.

2. PCA, as a commonly used method of data simplification and analysis, reflects the nature of features to some extent, establishes the coupling algorithm between PCA and CNN, and integrates PCA’s main feature extraction into CNN’s deep learning, which can realize the multi-layer feature fusion of shallow information features and deep features.

3. The accuracy of PCA and CNN coupling algorithm is 93.82% and 91.26% respectively, which are higher than that of traditional CNN algorithm, thus verifying the accuracy of PCA and CNN coupling model and its applicability in mineral phase identification.

4. For CNN model, the size of the sample set is directly related to the quality of the classification results, so it is important to master some methods of sample expansion to improve the accuracy of the results, therefore, the future research focus of this paper is the image sample expansion method.

### REFERENCES

[1] H. Yang, *Study on Improved SVM Model for Prediction of Pellet Metallurgical Properties*. Tangshan, China: North China Univ. of Technology, 2018.

[2] X. G. Ma, W. Zhang, and X. Q. Gao, “Determination and analysis of mineral composition and structure of sinter?” Shandong Metall., vol. 25, no. 3, pp. 32–34, Feb., 2003.

[3] A. Yang, Y. Li, C. Liu, J. Li, Y. Zhang, and J. Wang, “Research on logistics supply chain of iron and steel enterprises based on blockchain technology,” Future Gener. Comput. Syst., vol. 101, pp. 635–645, Dec. 2019, doi: 10.1016/j.future.2019.07.008.

[4] Z. Z. Wang, “Study on the structure of two-layer ore phase of pellets,” Sinter Pellets, vol. 2, pp. 1–7, 1989.

[5] Y. M. Chen and R. Chen, *Microstructure of Sintered Pellets*. Changsha, China: Central South Univ. Press, 2011.

[6] G. P. Luo, B. Zhao, and J. Q. Liu, “Study on phase structure and metallurgical properties of MgO bearing pellets at Baotou Steel,” Sinter Pellets, vol. 40, no. 57, pp. 25–27, May 2015.

[7] M. M. Ding, J. Li, and F. B. Kong, “Analysis of phase characteristics of magnesia flux pellets,” Chem. Des. Commun., vol. 44, no. 6, pp. 90–91, Jun. 2018.

[8] J. J. Sun and F. H. Wang, “Fractal analysis of wood fracture surface based on image processing,” J. Instrum., vol. 34, no. 12, p. 28, Oct. 2013.

[9] T. Q. Sun, Y. X. Yi, and J. Dong, “Prediction of sintering quality based on machine vision and neural network,” Comput. Eng., vol. 34, no. 11, pp. 240–242, Nov. 2018.

[10] F. Zhou, Y. W. Cen, and P. M. Du, “Fuzzy identification method for on-line determination of sinter sintering endpoint,” Instrum. User, vol. 10, no. 5, pp. 46–49, May 2013.
[11] D. J. Du, C. Z. Shen, and D. Y. Qiu, “Application of fuzzy threshold segmentation algorithm in image processing of sinter tail section,” Comput. Develop. Appl., vol. 17, no. 12, pp. 24–25, Oct. 2004.

[12] A. Krizhevsky, I. Sutskever, and G. Hinton, “ImageNet classification with deep convolutional neural networks,” in Proc. NIPS. Vancouver, BC, Canada: Curran Associates Inc., 2012, pp. 1097–1105.

[13] L. Zhang, G. Zhou, Y. Han, H. Lin, and Y. Wu, “Application of Internet of Things technology and convolutional neural network model in bridge crack detection,” IEEE Access, vol. 6, pp. 39442–39451, 2018, doi: 10.1109/ACCESS.2018.2855144.

[14] J. Zhang, Y. Jia, D. Zhu, W. Hu, and Z. Tang, “Study on the situational awareness system of mine fire rescue using faster Ross Girshick-convolutional neural network,” IEEE Intell. Syst., vol. 35, no. 1, pp. 54–61, Jan. 2020, doi: 10.1109/MIS.2019.2943850.

[15] A. Yang, Y. Zhuansun, Y. Shi, H. Liu, Y. Chen, and R. Li, “IoT system for pellet proportioning based on BAS intelligent recommendation model,” IEEE Trans. Ind. Informat., early access, Dec. 18, 2019, doi: 10.1109/TII.2019.2960600.

[16] G. Liu, X. Gao, D. You, and N. Zhang, “Prediction of high power laser welding status based on PCA and SVM classification of multiple sensors,” J. Intell. Manuf., vol. 30, no. 2, pp. 821–832, Feb. 2019.

[17] F. Y. zhou, L. P. Jin, and J. Dong, “Review of research on convolutional neural network,” Acta Comput. Sinica, vol. 40, no. 6, pp. 1229–1251, Oct. 2017, doi: 10.1109/ACCESS.2018.2855144.

[18] Y. Y. Hong, R. H. He, and M. Li, “Clothing image retrieval method combining convolutional neural network multi-layer feature fusion and K-means clustering,” Comput. Sci., vol. 46, no. 6, pp. 215–224, Jun. 2019.

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