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Metallographic Analysis of Spheroidization Using Deep Learning Neural Network

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Spheroidization is a process that uses a high temperature to change the properties of metals and it is often used in physical metallurgy. Metallographic inspection is an important method of inspecting the quality of metal materials after spheroidization. In the process of metallographic inspection, a high-power optical microscope combined with a digital camera is usually used to obtain an image of the spheroidized metal. A light sensor, which is a charge-coupled device in the camera, is used to convert the image observed by the microscope into an electronic image signal. In this paper, we present an image recognition method with a deep learning neural network (NN) to inspect the metallographic grade of spheroidized metal. Three different transfer learning models are incorporated in the NN structure for feature extraction for comparison. The overall aim of our study is to reduce the shortcomings and inconvenience of traditional manual inspection and increase the judgment accuracy of metallographic analysis. In experiments, 203 metallographic images of size 1536 × 2048 were used for the learning and testing of the NN. The metallographic grade of the spheroidized metal was evaluated using the deep learning NN model.

1. Introduction

Spheroidizing annealing is a well-known heating method for aggregating cementite steel into spheroids and uniformly distributing them in a ferrite matrix. Such an annealing process can improve the ductility of steel and reduce its hardness, so that the steel can be easily machined or deformed. The effects of holding time during both austenization and spheroidization on the microstructure and mechanical properties of high-carbon martensitic stainless steel 8Cr13MoV were experimentally studied by Yu *et al.*[(1)] Di *et al.* proposed a spheroidization procedure for eutectic carbide in a twin-roll-cast M2 high-speed steel strip that involved annealing, quenching, and tempering.[(2)] Studies on the changes in the mechanical properties of steel after spheroidization have also been presented.[(3–12)]

The spheroidization inspection methods used in industry can basically be divided into two types. In the first type, quantitative analysis is used to calculate the spheroidization rate, and in

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the second type, a metallographic diagram is compared with the standard diagram for judgment. However, both methods mainly involve manual tests. Such manual tests can only be carried out by sampling testing, and comprehensive testing cannot be achieved. Therefore, the true accuracy of testing is unclear. Here, we take a metal wire of 12 mm diameter as an example. For this wire, the total inspection area is about 113 mm^2. The area of the metal viewed under a microscope with a magnification of 500 times is about 12000 μm^2. In other words, it is necessary to inspect about 9400 pieces of this metal wire. Such manual inspection would be time-consuming and laborious, and only partial inspection, i.e., sampling inspection, can be carried out. Thus, the grade of the spheroidized metal obtained from metallographic analysis is only a verification result obtained from partial sampling rather than a comprehensive result. Because the result of the overall metallographic inspection cannot be accurately known in the case of sampling, deviations may be easily overlooked, affecting the quality of subsequent product production.

In this study, we propose an artificial intelligence (AI) image processing method to inspect the grade of spheroidized metal. A neural network (NN) model with deep learning is established to replace the process of manual judgment, so that the grade of spheroidized metal can be quickly determined over a large area. The proposed method and experimental results will be reported in the following sections.

2. Literature Review

In recent years, the use of AI image recognition in metallographic inspection has been explored, and related studies have also been published. Azimi *et al*. proposed a deep learning method for microstructural classification of low-carbon steel. A fully convolutional neural network accompanied by a max-voting scheme was implemented in their classification.[13] They concluded that the proposed system can achieve high classification accuracy, drastically outperforming the state-of-the-art method. Wu *et al*. proposed a novel convolutional neural network architecture based on a modified residual neural network (ResNet) for metallographic analysis.[14] They found that the multi-scale ResNet and the modified method can improve the detection accuracy. Xu *et al*. used the deep learning method in research on material recognition and the classification of metallographic images. Their two classification algorithms based on a convolution neural network and hierarchical transfer learning achieved good results for material recognition and the grading of metallographic images, respectively.[15] Other studies using NN technology in metallographic analysis have also been reported.[16–18]

3. Research Methods

3.1 Deep learning NN modules

In this study, three transfer learning methods are used for feature extraction, namely, VGG16, VGG19, and Xception. After the feature extraction of the migration model, each image is passed through a convolutional layer with 16 3 × 3 filters and one sub-sampling step. A fully connected layer (dense layer) with 1024 nodes is connected to the classifier as the final output layer. The number of nodes in the output layer is based on the number of categories that need to be classified. The basic structure of the deep learning NN model in this study is shown in Fig. 1. The operating processes of the VGG16, VGG19, and Xception modules are presented in Figs. 2–4, respectively.

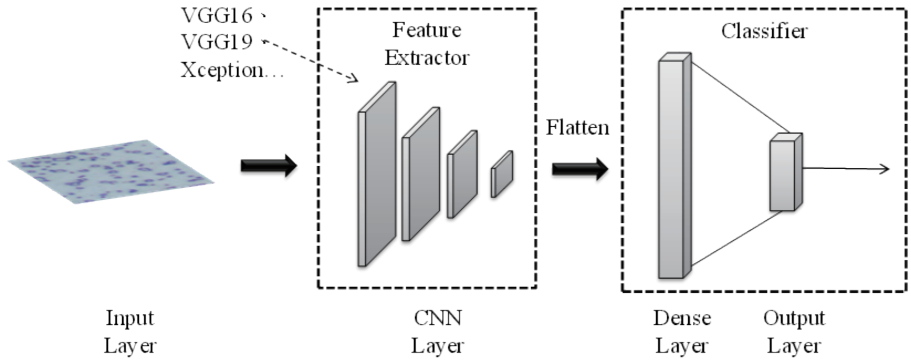

Fig. 1. (Color online) Basic structure of deep learning NN module.

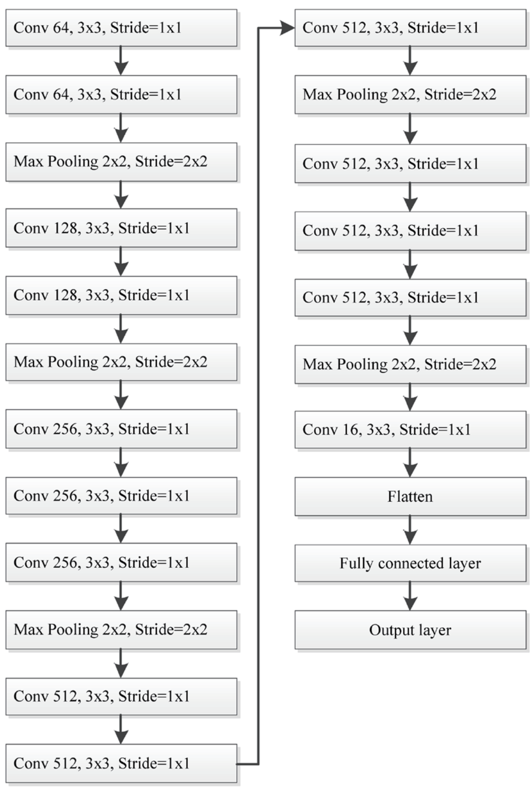

Fig. 2. Operating process of VGG16 module.

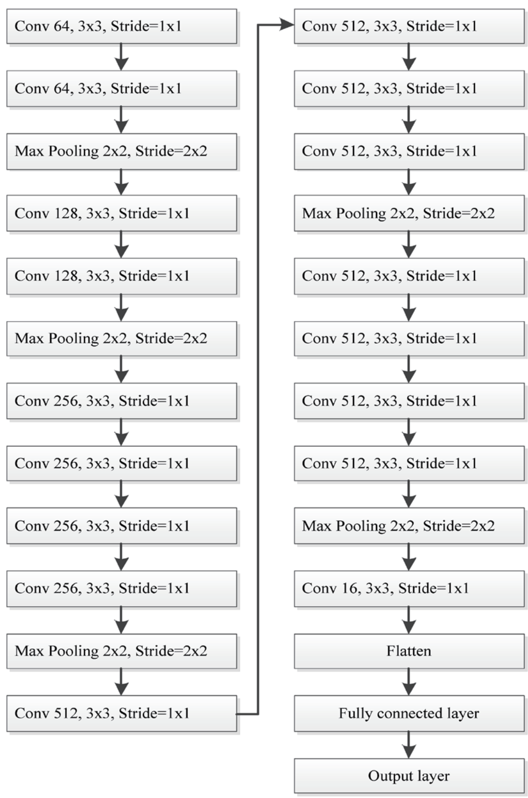

Fig. 3. Operating process of VGG19 module.

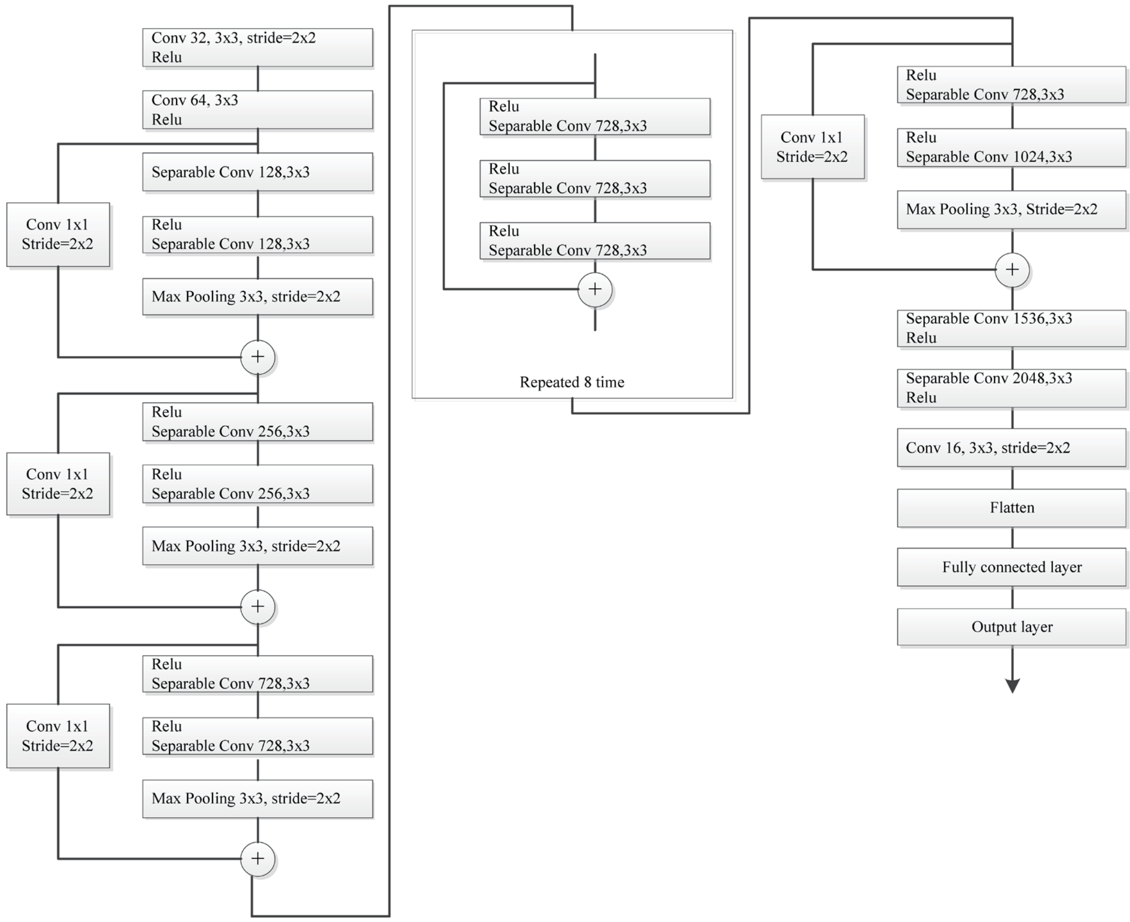

Fig. 4. Operating process of Xception module.

3.2 Measurement

Accuracy is often used as an indicator of measurement in many experiments. It is the simplest and most common measurement indicator. However, the accuracy may be distorted when the distribution of category labels is unbalanced. For instance, suppose there are four grades of spheroidized metal to be classified, and the number of each grade is Grade 1: 10, Grade 2: 80, Grade 3: 5, Grade 4: 5. If the classification model predicts all of them as Grade 2, then an accuracy of 80% can be easily achieved, and it is difficult to know whether the classification model is good or not. To avoid such ambiguity in evaluating measurement accuracy, measurements of precision and recall rates are also considered in this study.

For a two-class prediction problem, the outcomes are usually labeled either as positive (P) or negative (N). Therefore, four possible outcomes can be generated from a binary classifier. If the outcome from a prediction is P and the actual value is also P, then it is called a true positive (TP); however, if the actual value is N, then it is said to be a false positive (FP). Conversely, a true negative (TN) occurs when both the prediction outcome and the actual value are N, and a false negative (FN) occurs when the prediction outcome is N while the actual value is P.

Here, accuracy, precision, and recall are defined as follows.
Accuracy:

$$\frac{TP+TN}{TP+FN+FP+TN} \tag{1}$$

Precision:

$$\frac{TP}{TP+FP} \tag{2}$$

Recall:

$$\frac{TP}{TP+FN} \tag{3}$$

From Eqs. (1) and (2), it can be seen that the higher the FN and FP values, the lower the accuracy. To achieve higher accuracy in metallographic prediction, misclassification must therefore be avoided. In this case, the value of FP must be relatively small. Similarly, from Eq. (3), for a higher recall value, the FN value must also be as small as possible.

4. Experiments

In this study, 203 images of spheroidized metal of different grades (Grade 1–Grade 4) of size 1536 × 2048 pixels were collected and experimented on. To objectively compare the performance of the three different modules, the 203 data were randomly reorganized into five groups. The numbers of training and testing data for each grade are listed in Table 1. Figure 5 shows examples of metallographic images showing spheroidized metal of Grade 1 to Grade 4.

Table 2 shows the average accuracy rates of the experiment for the three modules. The average accuracy rates of the VGG16-based, VGG19-based, and Xception-based modules can reach 84, 84, and 82%, respectively. Tables 3 and 4 respectively list the precision and recall rates of the three modules in the verifications. It was found that the VGG19 module has the best performance in metallographic analysis.

Table 1
Numbers of images of Grade 1–Grade 4.

Data	Grade 1	Grade 2	Grade 3	Grade 4	Total
Training	57	73	15	9	154
Testing	18	24	5	2	49

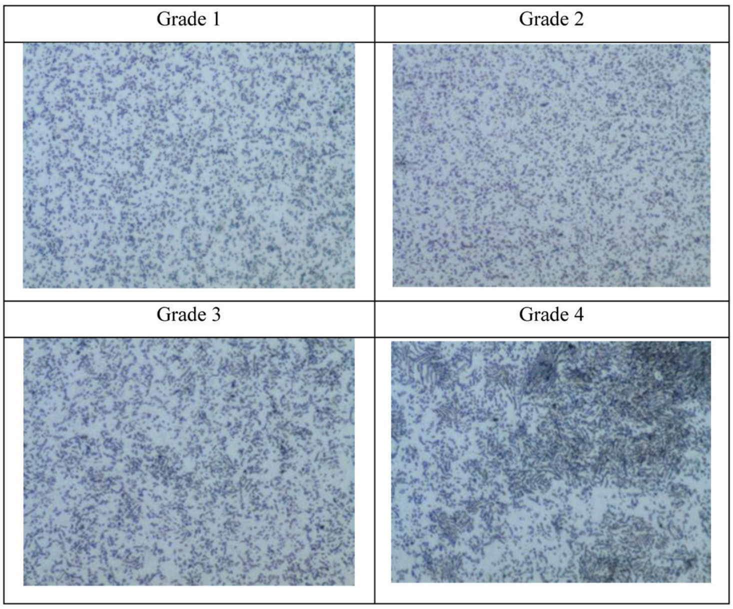

Fig. 5. (Color online) Examples of metallographic images of Grades 1 to 4.

Table 2
Accuracy rates obtained by the three modules.

	Accuracy					
	VGG16		VGG19		Xception	
	Training (%)	Validation (%)	Training (%)	Validation (%)	Training (%)	Validation (%)
Group 1	92	86	89	92	90	82
Group 2	83	86	94	86	88	78
Group 3	90	76	90	82	95	88
Group 4	86	84	88	86	88	80
Group 5	91	86	71	73	91	80
Average	88	84	86	84	90	82

Table 3
Precision rates obtained by the three modules.

	Precision					
	VGG16		VGG19		Xception	
	Training (%)	Validation (%)	Training (%)	Validation (%)	Training (%)	Validation (%)
Grade 1	100	99	91	91	98	95
Grade 2	82	79	86	84	87	79
Grade 3	87	62	80	72	93	70
Grade 4	100	93	100	90	83	63

Table 4
Recall rates obtained by the three modules.

	Recall					
	VGG16		VGG19		Xception	
	Training (%)	Validation (%)	Training (%)	Validation (%)	Training (%)	Validation (%)
Grade 1	77	77	89	90	88	78
Grade 2	97	94	85	85	96	91
Grade 3	81	56	77	56	69	40
Grade 4	100	80	98	80	100	100

5. Conclusions

The main purpose of this study was to develop an effective technique for metallographic analysis, which is an important step in detecting the quality of the steel spheroidization process. In the study, different grades of metallographic images were collected, and then three deep learning NN modules were used to evaluate the metallographic structure. In the experiments, we found that the three NN modules had good evaluation results, and the modules based on VGG16 and VGG19 had similar performance. The average validation accuracy of the modules reached 84%. This means that the shortcomings and inconveniences of traditional manual inspection methods can be greatly reduced, and the accuracy of metallographic analysis can be increased.

The spheroidization process is used to aggregate the cementite of steel into spheroids, which should be uniformly distributed in the metal. However, under actual conditions, cementite will not be uniformly distributed in the metal. Therefore, the boundaries and differences between different metallographic grades make analysis more difficult. In future research, we plan to divide a metallographic image (1536 × 2048) into 48 small images with a size of 256 × 256. Each small image will first be classified, then all the small images will be used for training and testing of the NN. Finally, the metallographic analysis of each original image will be judged on the percentage of images satisfying each grade. We believe that this method can further increase the accuracy of metallographic analysis.

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