Classification of Steel Microstructure Image Using CNN

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Abstract. The purpose of this study is to create a computerized system that can automatically evaluate microstructure images of steel materials, specifically focusing on ferrite, using a Convolutional Neural Network (CNN) model. Steel materials play a crucial role in our everyday lives, and their mechanical properties and reliability are determined by their microstructure, which is influenced by heat treatment and processing. It is essential to ensure the quality of steel, as problems can arise if the microstructure and mechanical properties are not adequately assessed before shipping. To accomplish this, the study involved preparing four different steel specimens with varying material properties and heating conditions, which were then photographed using a digital camera. The proposed CNN model was tested and validated to accurately classify the ferrite substances, and it was found that even a simple CNN structure could achieve high accuracy in image classification. The implementation of this system will alleviate the burden of human visual inspection. The paper provides detailed information on the preparation of the steel specimens, the method used to capture the images, the structure of the proposed CNN model, the experimental conditions, the validation methods employed, and the results obtained.

Keywords: Steel · Ferrite · Microstructure · CNN

1 Introduction

Steel materials are indispensable for our life infrastructures such as buildings, land transportation infrastructure, maritime infrastructure such as ships, and magnetic circuits of generators and induction motors.

Given the wide range of uses for steel, steel quality control is essential. Steel mechanical properties and reliability depend on their microstructure, controlled by heat treatment and processing. For instance, quenching is a common heat treatment method used to transform the structure of steel materials into the martensite phase, improving hardness and strength. However, the strength would be insufficient if the necessary part did not transform into the martensite phase. If the microstructure and mechanical properties are not sufficiently assessed before shipping, it could cause significant problems. The metal additive manufacturing techniques employed in 3D printing simultaneously

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control shape and microstructure [1, 2]. Therefore, the quality control of steel products is important throughout the manufacturing process, including metal 3D printers. Mechanical properties are generally evaluated by destructive tests such as tensile and bending tests. In addition, a human evaluator inspects optical microscopic images of the microstructure. However, since the evaluators must check the optical microscope images with their eyes, the physical burden is a problem, especially when dealing with many samples. Evaluation of microstructure images requires experience. Therefore, the present paper aims to develop an automatic evaluation system for microstructure images of metallic materials obtained from optical microscope using CNN (CNN: Convolutional Neural Network), which has high capabilities in image recognition [3]. To evaluate various materials, CNN can automatically acquire the important features from many steel material texture images. The proposed system will not only reduce the human visual inspection burden, but also save time, and thereby allows for rapid feedback to the manufacturing process.

Several studies [4–6] in material science have utilized Neural Network (NN) and Convolutional Neural Network (CNN). Specifically, study [4] aims to find important processing factors e.g., laser power using NN to compound aluminum and magnesium alloys. Additionally, the study [5] focuses on accurately segmenting crystal grain regions in aluminum alloy images for evaluation purposes, using semantic segmentation. In the study [5], CNN is employed to generate feature maps. Lastly, in the study [6], GNN (GNN: Graph NN) is applied to discover new material compositions.

There is a study [7] that evaluates the microstructure of steel materials. However, there are still few studies that automatically evaluate the size of ferrite grains and the differences in microstructure within the same sample. In the present paper, the authors aim to automatically evaluate steel microstructure images using a simple CNN model, as a first step towards realizing an automatic steel quality evaluation system. We prepared four steel specimens by changing the material properties and heating conditions.

In Sect. 2, we will discuss the preparation of the specimens and the method of image capture. Section 3 will describe the structure of the simple CNN proposed in this paper. In Sect. 4, we will discuss the evaluation experiments of the CNN. Finally, in Sect. 5, we will present the conclusions and discuss future challenges.

2 Preparation of Specimen and Pictures

Two alloys, Fe-1Mn-0.1C and Fe-1Mn-0.1C-1Si, were selected and prepared by weighing pure Fe, pure Mn, carbon, and pure Si to achieve these compositions, using the vacuum arc melting method. Two different heat treatments were applied to these two compositions of alloys, resulting in four types of specimens with different ferrite grain sizes, as followings.

Specimen A: Fe-1Mn-0.1C, annealed at 1150 °C for 1 h, then furnace cooled.
Specimen B: Fe-1Mn-0.1C-1Si, annealed at 1150 °C for 1 h, then furnace cooled.
Specimen C: Fe-1Mn-0.1C, annealed at 1150 °C for 1 h, then quenched in ice water, followed by tempering at 750 °C for approx. 2 minutes, then air cooling again.
Specimen D: Fe-1Mn-0.1C-1Si, annealed at 1150 °C for 1 h, then quenched in ice water, followed by tempering at 750 °C for 5 min, then air cooling again.

The specimens were cut out using an electrical discharge machine, then polished with waterproof abrasive paper, followed by electrolytic polishing. They were then etched to produce the final specimens. These specimens were observed under an Olympus BX51 microscope with a 100× magnification, using a DP-22 digital camera. The images of Specimens A to D are shown in Fig. 1.

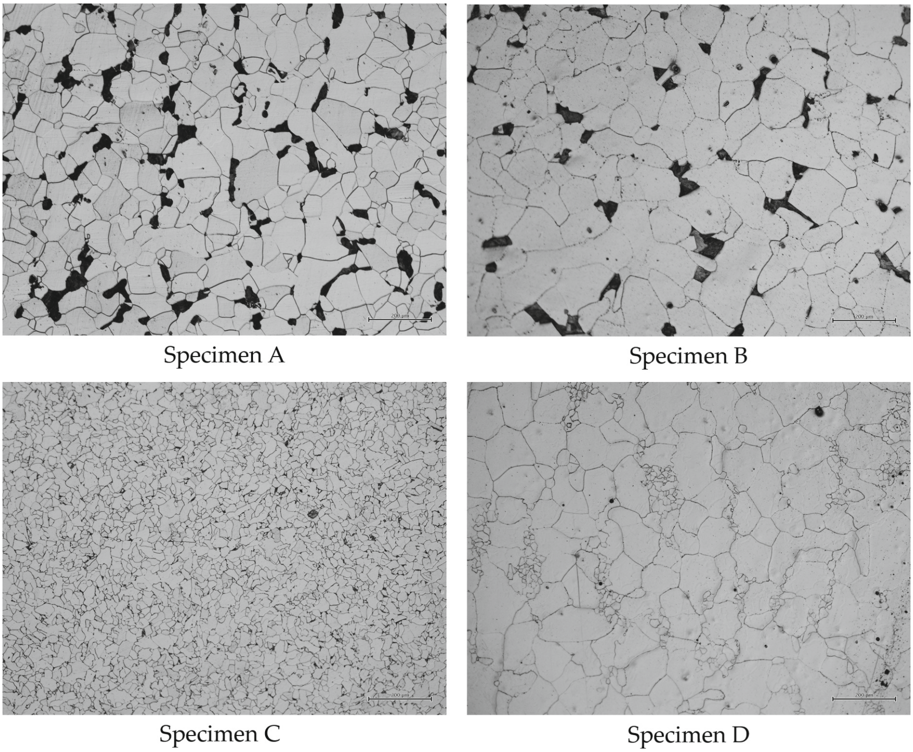


Fig. 1. Pictures of four specimens captured by microscope.

Specimen A has a composition of Fe-1Mn-0.1C and underwent annealing at 1150 °C for 1 h. Specimen B has a composition of Fe-1Mn-0.1C-1Si and underwent annealing at 1150 °C for 1 h. Specimen C has a composition of Fe-1Mn-0.1C and underwent annealing at 1150 °C for 1 h, followed by quenching after approx. 2 min of tempering. Specimen D has a composition of Fe-1Mn-0.1C-1Si and underwent annealing at 1150 °C for 1 h, followed by quenching after 5 min of tempering. Both specimen C and D were cooled in air after tempering.

The image in Fig. 1 is a monochrome image in TIFF format with a resolution of 1440 × 1920 pixels and unsigned int 8bit depth. This was converted into an image in bitmap format with unsigned int 8 bit depth. For each of the Specimens A, B, C, and D, ten images were obtained. Next, as shown in Fig. 2, each image was divided into four parts, generating 4 × 10 = 40 images for each specimen.

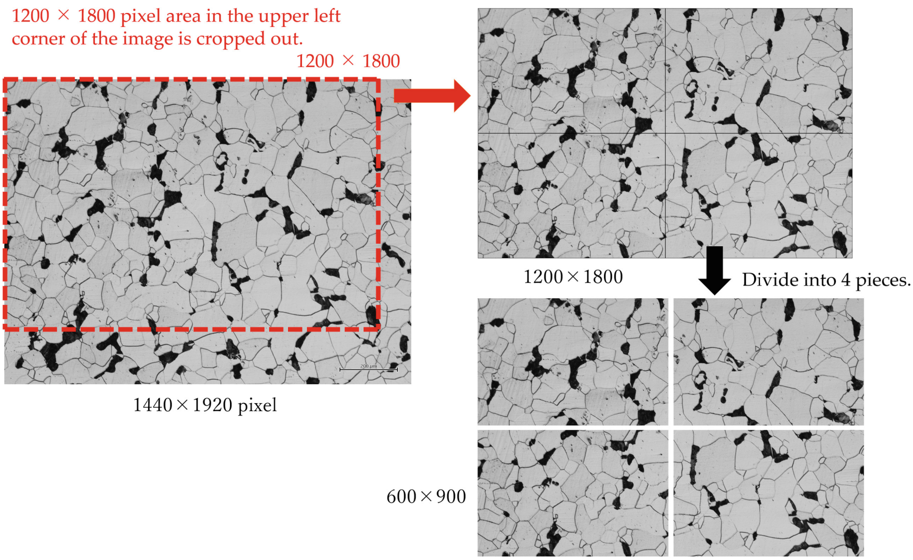


Fig. 2. Each picture is divided into four images.

As shown in Fig. 2, the top left 1200 × 1800 section was divided into four parts, obtaining four images of 600 × 900 pixels from one original image. By doing this for each of Specimens A, B, C, and D, a total of 160 image data were obtained. A Convolutional Neural Network (CNN) was constructed to determine whether each of the 160 images belonged to Specimen A, B, C, or D.

3 CNN Structure

As shown in Fig. 3, a Convolutional Neural Network (CNN) was constructed that takes as input an image of size 200 × 300 × 1 (reduced to one-third of the original size) and outputs the classification class of the specimen.

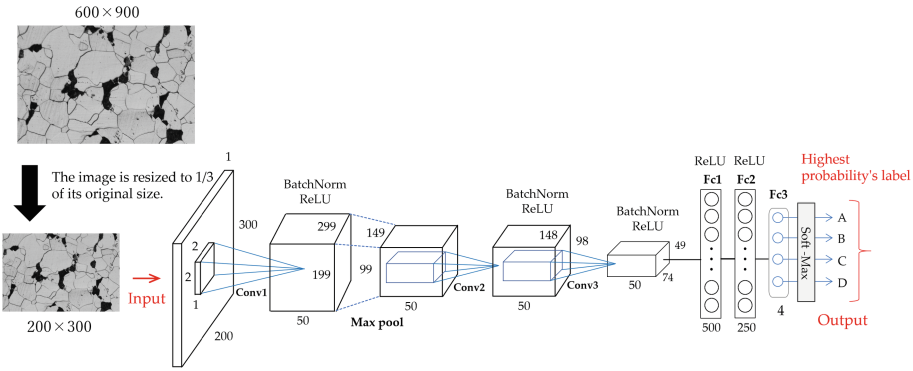


Fig. 3. Schematic of CNN classifying four specimens.

The details of the calculations in Fig. 3 are shown in Table 1.

Table 1. Details of operations at each layer

Layer name	Operation	Filters' set number	Filter Size	Stride	Output
Input	-	-	-	-	$200 \times 300 \times 1$
Conv1	Conv ->BatchNorm ->ReLU	50	$2 \times 2 \times 1$	1×1	$199 \times 299 \times 50$
Max pool	Max pooling	-	3×3	2×2	$99 \times 149 \times 50$
Conv2	Conv ->BatchNorm ->ReLU	50	$2 \times 2 \times 50$	1×1	$98 \times 148 \times 50$
Conv3	Conv ->BatchNorm ->ReLU	50	$2 \times 2 \times 50$	2×2	$49 \times 74 \times 50$
Fc1	Affine ->ReLU	-	-	-	500
Fc2	Affine ->ReLU	-	-	-	250
Fc3	Affine ->Soft-Max	-	-	-	4

The Convolutional Neural Network (CNN) [3] is a machine learning algorithm proposed by Yann LeCun, which allows for high-accuracy image recognition with low computational cost. By performing Batch Normalization (BatchNorm) [8] after convolution operations, it is possible to improve the efficiency of learning, omit processes such as Drop Out [9], and simplify the system. Furthermore, by using the ReLU [10] function as the transfer function, it is possible to prevent gradient loss of the error function and enhance the classification performance.

4 CNN Validation

This section explains an experiment to validate the CNN shown in Fig. 3 using 160 image data. It is not always feasible to obtain a sufficient amount of data to evaluate the performance of a machine learning model. For instance, collecting image data like medical data from CT scans or images taken with an electron microscope can often be challenging. For these reasons, several methods have been proposed for evaluating models with limited data [11].

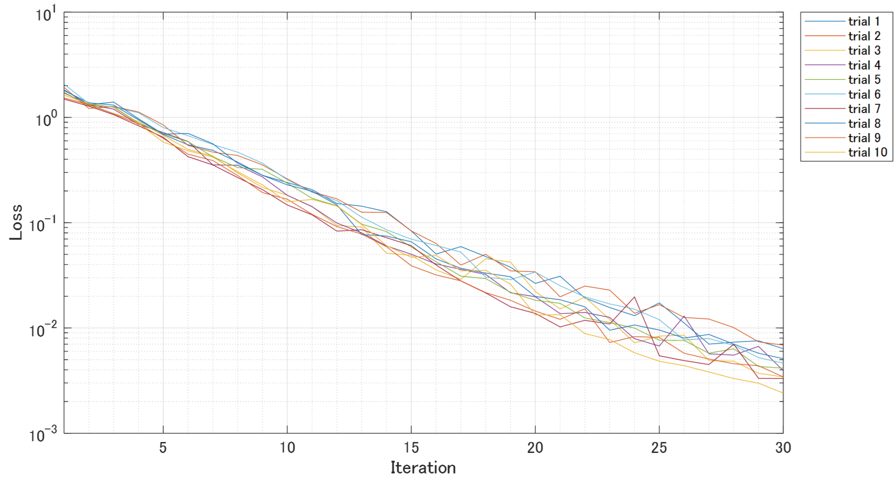
In this study, we were able to obtain 160 images to validate the CNN model, but this is not sufficient as training data for deep learning models. Therefore, we repeatedly performed random subsampling validation. The dataset contains 40 images each of Specimens A to D. Five images from each class were randomly selected and set aside as test data, while the remaining 140 images were used for training the CNN. After training, the unused 20 images were used as a test set to verify the classification accuracy of the CNN. In this study, this process was performed 10 times to evaluate the performance of the CNN.

Table 2 shows an overview of the learning conditions for the CNN. Horizontal and vertical flipping of the training images is performed at random probabilities. This process allows the model to virtually learn from a larger number of images [12].

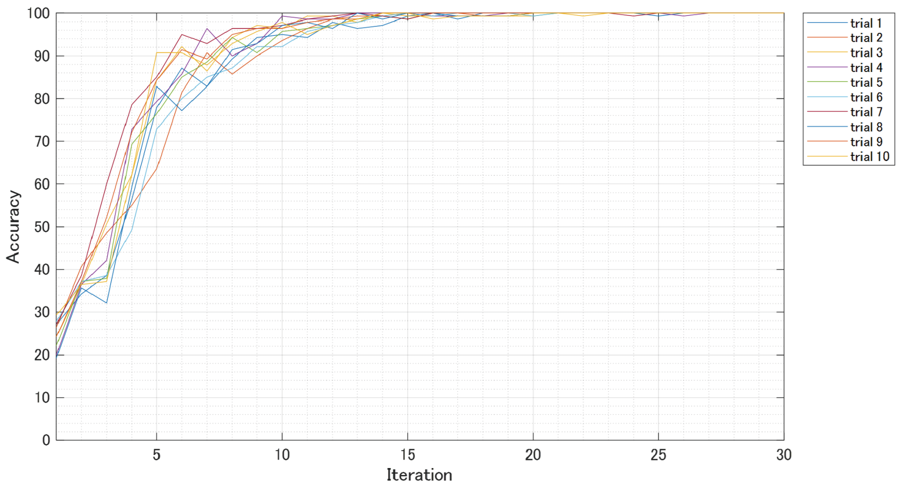
Table 2. Training conditions for CNN

Items	Value
Solver	SGDM (Stochastic Gradient Descent with Momentum)
Learn Rate	10^{-3}
Total Iterations	30
Mini batch Size	512
Augmentation	Random Left-Right Reflection (50%), Random Top-Down Reflection (50%)
CPU	Intel core i9 12900K
Main Memory	128 GB
OS	Windows 11 Pro 64bit
Development Language	MathWorks, MATLAB
GPU	Nvidia RTX A6000 (VRAM 48 GB, 10752 cuda cores)

The training uses the backpropagation method [13], and the cross-entropy error [14] is used for the calculation of loss. Figure 4 shows the transition of loss and accuracy during training for each of the 10 trials.



(a) Loss transition in learning process

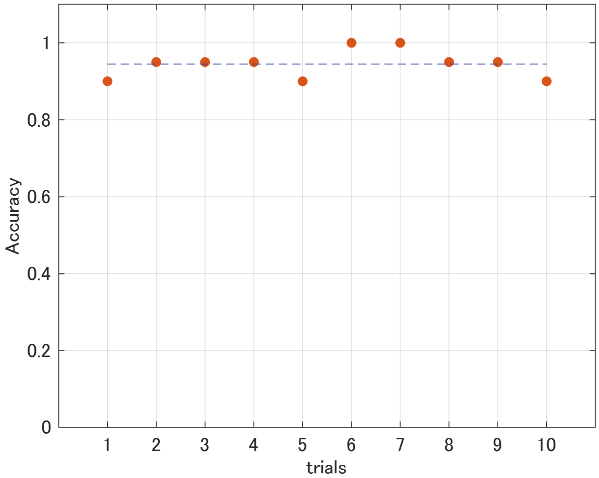


(b) Accuracy transition for training data during learning

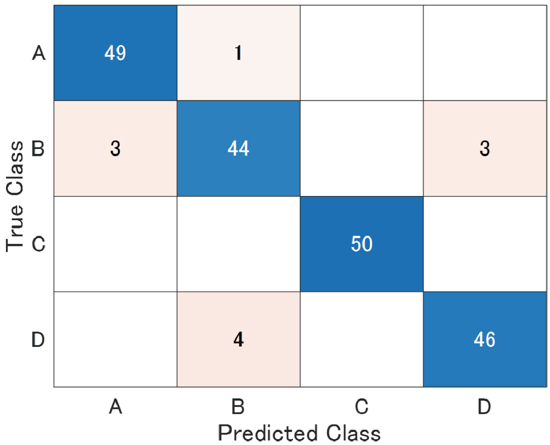
Fig. 4. Training result.

As shown in Fig. 4 (a), the loss has decreased to the order of 0.01, confirming that there are no issues with the training. Also, from Fig. 4 (b), it can be seen that the accuracy has reached 100% for all 10 trials, confirming that the model can correctly classify all the training data.

The accuracy when the 20 test images, which were not used in the training, were input into the trained CNN is shown in Fig. 5(a). The average accuracy was 94.5%. Also, the confusion matrix for all trials is shown in Fig. 5(b).



(a) Accuracy in each trial



(b) Confusion matrix for all 10 trials

Fig. 5. Test result.

It can be seen that Specimens A and B, which are similar, are being misclassified. Even with such a shallow CNN, it was confirmed that it is possible to distinguish images of different steel crystals with high accuracy. In the future, it will be necessary to construct a CNN to determine the quality of crystal compositions.

5 Conclusion

In this study, we attempted to distinguish between four types of crystals created using different compositions and heat treatments using a Convolutional Neural Network (CNN). Initially, different heat treatments were performed on specimens of different materials.

The surfaces of these were polished, and images were taken with an optical microscope for each of the four different specimens, resulting in ten images per specimen.

To verify whether crystals can be classified using a CNN, a large amount of data is needed. Therefore, each image was divided into four parts to increase the amount of image data. Also, during training, we devised a method to virtually increase the number of training images by performing processes such as flipping images vertically and horizontally. Despite the small amount of training data, the loss was confirmed to have decreased to the order of 0.01, indicating that adequate learning was achieved.

We conducted 10 trials using 20 test images that were not used in the training process, and in all cases, CNN could accurately classify into four categories. These results demonstrate the feasibility of constructing a Convolutional Neural Network (CNN) to determine the quality of crystal composition. The next challenge is to increase the data and construct a model that can estimate strength.

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