

# Development of Deformed Steel Bar Counting Machine Using Deep Learning

IKEDA Takayuki

## Abstract:

*JFE Plant Engineering Co., Ltd. has developed a steel bar counter that counts the number of steel bars in a bundle of deformed steel bars. By applying AI (Artificial Intelligence) to the counting algorithm, this device has achieved a higher accuracy rate than existing image processing methods. Based on this high discrimination ability, a unique method has been adopted for the structure and operation of the device and the display of the processing results, significantly reducing the burden of the comprehensive inspection work of steel bundles before shipping. In this report, we introduce a method of applying AI to industrial sensors that require high performance and a unique function for making a comprehensive judgment of the bundles. Although five years have passed since the device was put into operation, it continues to perform satisfactorily, contributing to ensuring product quality and reducing the workload of operators.*

## 1. Introduction

In recent years, higher accuracy and higher functionality have been achieved in various fields of industry by applying artificial intelligence (hereinafter referred to as AI) in an increasing number of cases<sup>1-4)</sup>. The AI applied in these cases is called “narrow AI,” and is characterized by a high response capability for similar tasks, which is acquired by training the AI on past data for a particular task, enabling the AI to grasp the features of the data autonomously.

JFE Plant Engineering Co., Ltd. developed a deformed steel bar counting machine utilizing this characteristic of narrow AI and applied the device in practical operations. The learning data for the device were generated from images of the end surfaces of a huge number of bundles of steel bars accumulated by conventional image processing-type counting machines, and high accuracy was achieved in counts of the num-

ber of bars by improving the performance level of the device while applied in actual operations. As unique functions, identification of badly-shaped steel bars, identification of bundles of steel bars mistakenly mixed with short steel bars of different dimensions and detection of bundles with uneven ends have also been achieved with high reliability. These functions allow the operator to grasp the condition of bundles from the operation room, contributing to ensuring product quality and reducing the workload on operators. This paper introduces the developed deformed steel bar counting machine.

## 2. Necessity and Problems of Steel Bar Counting Machines

### 2.1 Inspections before Bundle Shipment

Deformed steel bars are normally shipped in the form of bundles by binding a predetermined number of steel bars of the same length specified for each size. **Photo 1** shows an image of a D10 bundle (bundle of 400 steel bars with a diameter of approximately 10 mm).

In the manufacturing process, bundles are controlled so as to contain the specified number of bars, but there are cases where the number of bars is over or under the specified total due to material remaining in the binding machine, etc. as a result of equipment trouble or other causes. In addition to the number of bars, the following items are also checked visually as pre-shipment inspections.

- (a) Detection of steel bar bundles mixed with steel bars with poor end shapes which should have been rejected in the intermediate process, such as the head and tail end parts of billets with a semicircular spherical shape (hereinafter abbreviated as “semicircular sphere”) that lacks a metallic luster, or spear-like protruding ends (abbreviated as

<sup>†</sup> Originally published in *JFE GIHO* No. 56 (Aug. 2025), p. 35–40

Staff general manager, Measuring system Design Sec.,  
Control System Technology Dept.,  
Technology Development Center, Plant Div., JFE Plant Engineering

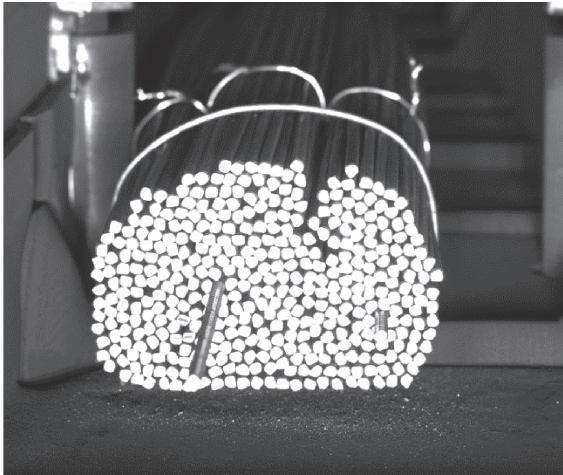


Photo 1 Image of a defective bundle of steel bars (Approximately 10 mm in diameter)

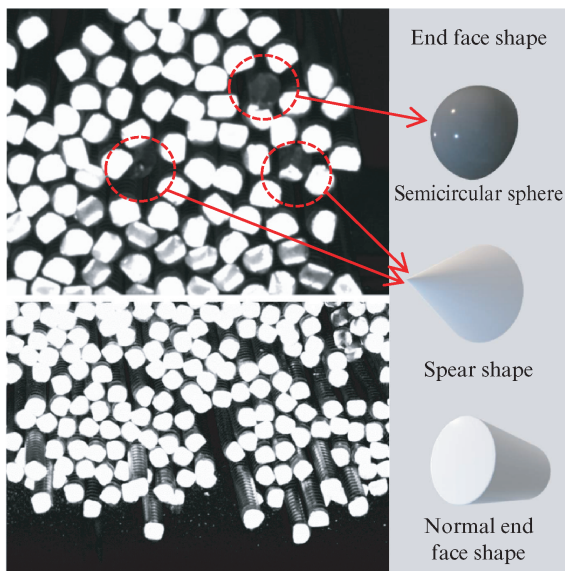


Fig. 1 Image of steel bar with poor end shape and bundles with uneven ends

“spear shape”) caused by primary cutting performed while traveling. Examples of these defects are shown in Fig. 1.

- (b) Check for bundles with uneven ends (misaligned bar ends or protruding bars).
- (c) Check for mistakenly mixed bars with short lengths (abbreviated as “short bars”).

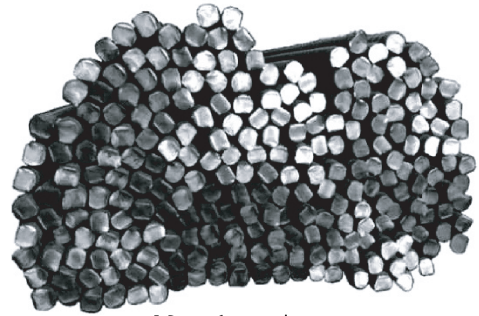
Since the objects of these inspections include bundles containing as many as several 100 steel bars, particularly in the case of small-diameter bars, and the inspections are performed visually on a regular basis, the accuracy of judgments and the large workload on the inspectors were problems.

## 2.2 Purposes of Applying AI

The deformed steel bar counting machine was intro-



Color image



Monochrome image

Photo 2 End surface of steel bar with temper color

duced for the purposes of improving the level of quality assurance and reducing the workload on operators. Initially, a conventional device using an image processing method was introduced, but it was not possible to improve the accuracy rate because that device could not respond completely to the temper color that occurs in small-diameter sizes.

Photo 2 shows images of a bundle in which temper color occurred. When steel materials are sheared in a high-temperature condition, a thin oxide film forms on the surface. Temper color is a phenomenon in which the color of the metal surface changes due to interference caused by the oxide film. Different colors appear depending on the shear temperature, as the surface appears brown when the material temperature is around 200°C and blue when the temperature is close to 300°C. However, since the material loses its metallic luster in either case, photographs taken with a camera appear extremely dark.

As one factor in the failure to improve the accuracy rate, the shapes and changes in the luster of steel materials that should be counted and those which are not to be counted are very similar. Typical problems include the difficulty of distinguishing between the dark background and steel bars that appear dark when photographed due to temper color or bar ends with a semi-circular spherical shape, distinguishing between a condition where only part of the bar surface appears bright due to a difference in the luminance of the end surface and bars which are hidden by other materials due to misalignment and are only photographed par-

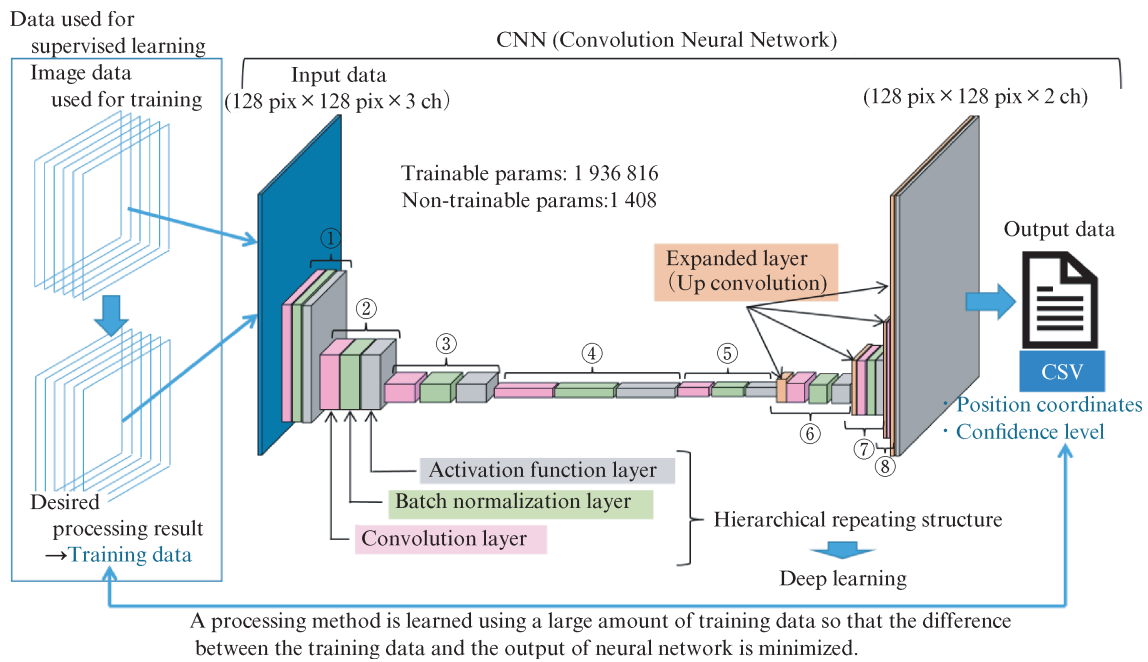


Fig. 2 CNN structure applied to bar counting machine

tially or bars with spear-shaped ends, etc.

Various methods of overcoming these problems have been tried. However, with the existing method, in which a developer designs and programs distinction rules, we judged that there were limits to the construction of the algorithm, and therefore applied AI, which allows a completely different approach from the conventional processes.

### 3. AI Applied to Steel Bar Counting Machine

#### 3.1 Applied AI

A Convolutional Neural Network (hereinafter abbreviated as CNN) was applied to the steel bar counting machine. Since CNN basically treats data by a 2-dimensional relationship of  $n \times m$ , it is frequently used in the image processing field<sup>5)</sup>. As the dataset used for supervised learning, “images” and “training data expressing the desired results of processing of images” were prepared, and CNN performed learning autonomously so as to minimize the difference between the CNN output and the training data, with the aim of automatically constructing a distinction algorithm suitable for this counting machine. The learning results were output as an inference model, making it possible to generate the desired output from completely new photographic images.

**Figure 2** shows the structure of the developed CNN. The input is images consisting of 128 pixels x 128 pixels x 3 channels (R, G, B), and the CNN has a hierarchical repeating structure that repeats the three processes of

“Convolution layer,” “Batch normalization layer”<sup>6)</sup> and “Activation function layer”<sup>7)</sup>. The features of this CNN include the following.

- (a) Unlike conventional CNN, a pooling layer is not provided; image resolution is reduced during convolution.
- (b) After repeating the series of processes of convolution - batch normalization - activation function 5 times to compress the image to 8 pixels x 8 pixels x 128 channels, an “Expanded layer” is included to return the image to its original size of 128 pixels x 128 pixels.

While structurally similar to U-Net<sup>8)</sup>, this CNN is different in that it does not contain a skip connection. The final output values of the CNN are “Positions (i.e., coordinates on the image) of steel bars that should be counted” and “Degree of similarity of attributes of the detected steel bar shape and attributes of the steel bar shape given as training data (i.e., confidence level: probability expressed by a numerical value between 0 and 1).”

The images captured by the cameras comprise 2 560 pixels x 2 048 pixels. However, due to the limitations of the GPU (Graphics Processor Unit) memory, the images are processed by cutting out 128 pixel x 128 pixel sections at a constant pitch, and the position information and confidence level of the steel bars are obtained from those sections. The obtained position information is finally recalculated in the position information on the photographed images.

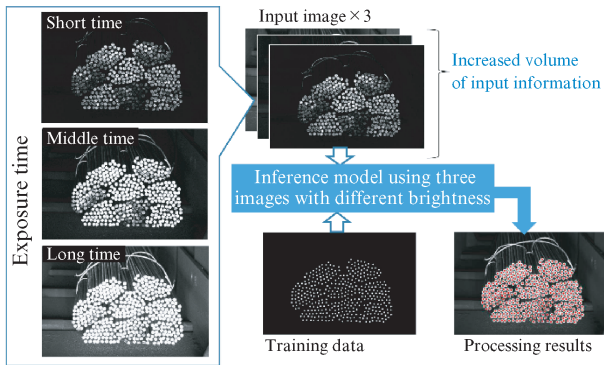


Fig. 3 Image of high dynamic range image process

### 3.2 Innovations to Improve Accuracy Rate in CNN

As shown in Photo 2 above, the subject steel bars include surfaces with a normal metallic luster, surfaces with low light reflectivity due to temper color and others, and the difference in brightness is extremely large. Since these conditions exceed the brightness range that can be reproduced by a camera (i.e., dynamic range), the information intrinsically required for judgments is lost, resulting in counting errors. Therefore, in this device, we adopted a CNN inputting method (High dynamic range image process<sup>9)</sup> in which three photographic images with different exposure times are treated as a set<sup>10)</sup>. The aim of this feature is to allow the CNN itself to extract the appropriate information from each image in the learning process and make comprehensive judgments based on that information. Verification showed that this method is extremely effective for improving the accuracy rate. **Figure 3** shows the image of the high dynamic range image process.

### 3.3 Preparation of Training Data

**Figure 4** shows an example of tagging annotation for preparation of the training data. The image data for training are tagged with yellow square marks at positions on the figure that are verified to be steel bars. The training data generated by this work are the figure positions of the bars that should be counted. To teach the CNN to recognize the shape information of badly-shaped steel bars, etc., figures that should not be counted are not tagged with these square marks. The left edge of Fig. 4 shows a spear-shaped bar (indicated by the red circle) which is suspected to be the remaining end face of a bar after primary cutting. This is an example where a bar is not tagged with a square mark so attributes of the figure will not be learned as steel bars.

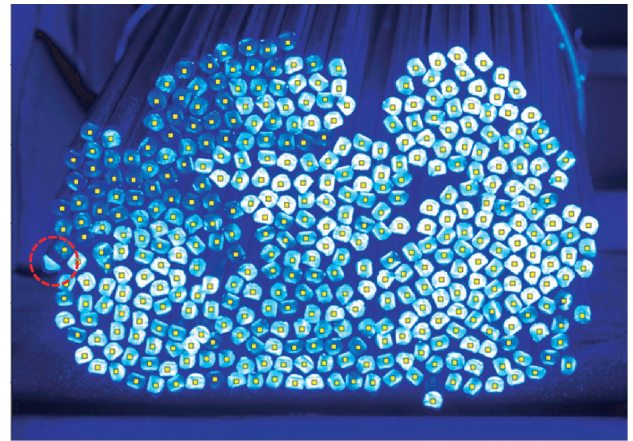


Fig. 4 Making training data

### 3.4 Learning

#### 3.4.1 Learning Data

In generating the learning data, first, a large number of images of badly-shaped steel bars and bundles containing misshapen steel bars were secured from the enormous number of past images stored by the conventional bar counters.

The aim was to construct an unbiased, robust inference model that accurately reflects the operation status from these images by repeatedly performing the following procedure:

- (1) Prepare a small-scale learning data and construct an inference model.
- (2) Apply the inference model to photographic images of bundles actually flowing in the process.
- (3) Identify the weaknesses of the model by collecting and analyzing incorrect images.
- (4) Add new images that include the weak points, and repeat the learning process.

Finally, 480 images in D10 size (containing a total of 192 000 steel bars) were required. The learning method adopted in this process was mini-batch learning, in which images are divided into multiple groups for use in learning. As features of the mini-batch method, because the number of data to be processed at one time is small, the processing results tend to respond sensitively to changes in the parameters, and learning is hard to stagnate. A categorical cross-entropy loss function in machine learning was used as the loss function to visualize the error between the training data and the CNN output, and Nadam (Nesterov-accelerated Adaptive Moment Estimation) was used as the optimizer algorithm to minimize the values of the loss function. One learning process using all the prepared learning data is called 1 epoch. In this system, 1 epoch using 480 images required a processing time of 27.5 minutes. In

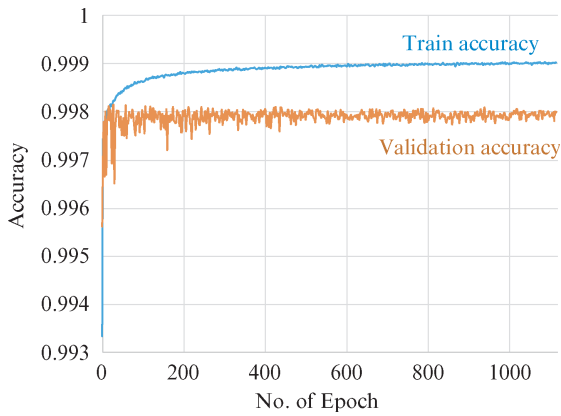


Fig. 5 Learning curve-Accuracy

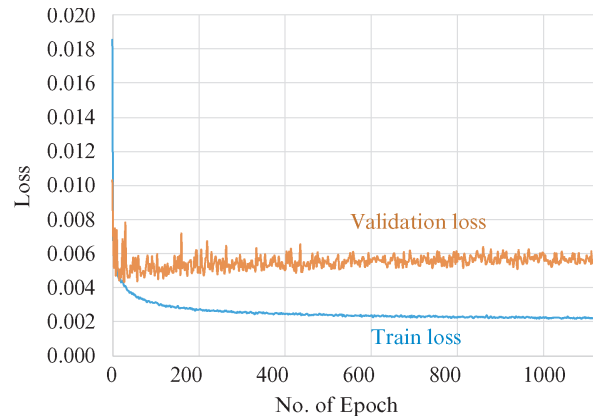


Fig. 6 Learning curve-Loss

total, 1 160 epochs were calculated, requiring a calculation time of 21 days.

### 3.4.2 Condition of Learning

The learning curves of the accuracy rate and loss are shown in Fig. 5 and Fig. 6, respectively. “Train accuracy” indicates the accuracy rate when the learned data were applied to the inference model obtained at the corresponding number of epochs. “Validation accuracy” is the accuracy rate when the inference model is applied to unknown image groups that were not used in learning, and represents the forecast accuracy of the model. “Train loss” and “Validation loss” shows the values of the calculated loss function, and is used in judging the progress of learning.

High values were obtained for Train accuracy (0.999) and Validation accuracy (0.998), and Validation accuracy converged as learning progressed. Loss also showed low values for both Train loss and Validation loss. However, the learning curves for loss displayed a typical overfitting condition, in which Validation loss does not decrease as learning progresses. As the cause of overfitting, because each image contained about 1 or 2 steel bars that were really hard to judge, but the other bars could be judged correctly by a simple algorithm, this was considered to be a case of “applying a complex model to a simple problem.” This can also be inferred from the fact that both Accuracy and Loss showed satisfactory values even at a small number of epochs. However, since the 1 or 2 hard-to-judge bars had an outsized influence on the accuracy rate of the bundle unit, the author did not make any changes to the processing in the CNN to resolve the overfitting condition.

### 3.4.3 Selection of Inference Model

In general, the model at the time of minimum Validation loss is frequently selected as the inference model. However, under the above-mentioned overfitting condition, this selection was not possible because the

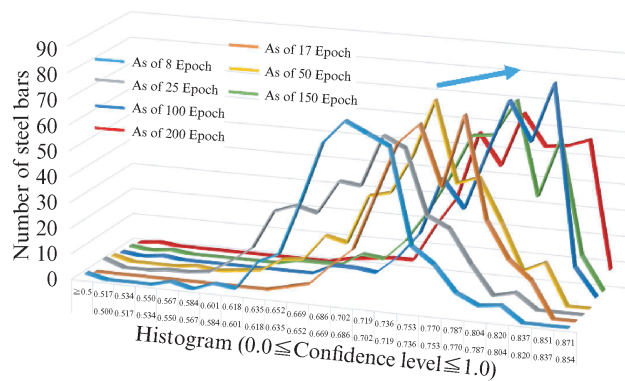


Fig. 7 Learning progress indicated by the distribution of probability

minimum timing occurred at a small number of epochs, where learning had not progressed.

Therefore, a histogram of the confidence level for 400 steel bars was prepared by applying the models at various points in time in the learning process to designated images with strong temper color, and a model with the number of epochs where the median value was high and the standard deviation was small was selected as the inference model. Figure 7 shows that the peaks of the histograms shift to the high confidence level side as learning progresses. For easier understanding, this figure shows the stage where the number of epochs is still small.

Figure 8 shows the coordinates and confidence level obtained by the inference model in the image, and the expanded image shows a part of the image where the confidence level was low due to a strong temper color. In counting the number of steel bars, the locations where the confidence level exceeds a certain value are judged to be positions where steel bars exist.

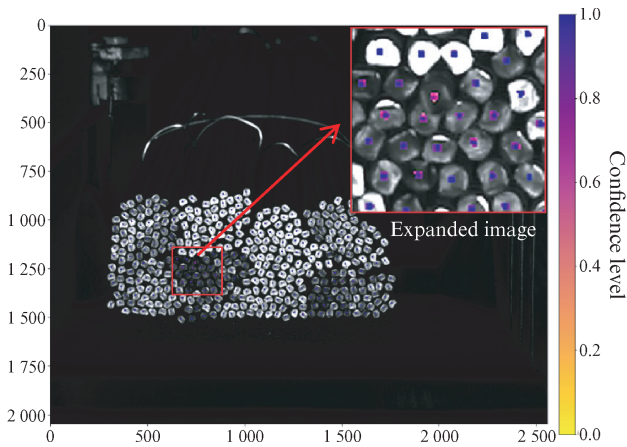


Fig. 8 Processing results based on inference model

Table 1 Comparison of correct answer rate

	Existing device	Applying CNN
D10 Correct answer rate (%)	99.3557	99.9982
D13 Correct answer rate (%)	99.4454	99.9988

## 4. Developed Steel Bar Counting Machine

### 4.1 Performance of CNN

Table 1 shows the accuracy rates of an existing image processing-type device and the developed CNN device, where the unit is the number of steel bars. The table shows the data for D10 and D13 (steel bar diameter: approx. 13 mm) as small-diameter sizes in which the effect of temper color is strong. The data are the results of a follow-up study of more than 4 million steel bars.

Converted to error per 100 000 steel bars, the number of counting errors for D10 was 640 with the conventional device, and decreased to 2 when the CNN was applied, and the number for D13 was 550, which decreased to 1, confirming a remarkable improvement in the accuracy rate.

### 4.2 Operation of Steel Bar Counting Machine and Detection of Nonconforming Materials

Figure 9 shows operation of the steel bar counting machine. The machine has a structure that counts bars both at the front end and rear end of the bundles. The cameras are positioned facing downward from slightly above to prevent recognition of recessed bars (bars that do not extend to the bundle end) by hiding those bars in the shadow of other bars. In contrast, in the lighting pattern, the bundle is illuminated directly from in front, prioritizing light directivity, in order to avoid confusion of the darkness of images due to insufficient light

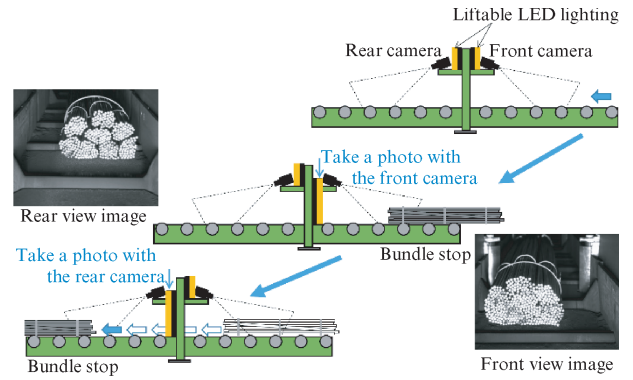


Fig. 9 Operation of steel bar counting machine

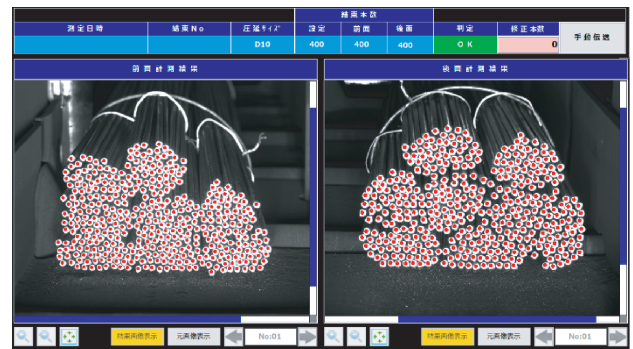


Fig. 10 Screen displaying count results

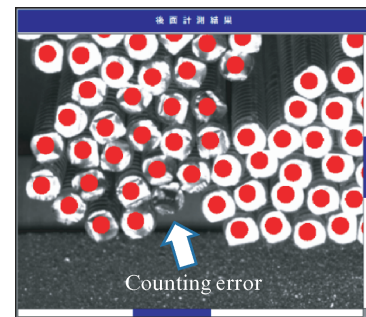


Fig. 11 Enlarged display of processing result

reaching the bundles with protrusion or recess of bars, and the darkness of the spear shape and semicircular spherical shape, which lack a bright metallic luster.

A screen displaying the count results is shown in Fig. 10. Bar locations where a certain confidence level was obtained are shown by solid red circles, and the screen indicates that the count has been completed. This screen can be enlarged as shown in Fig. 11, making it easy to check the cause when the count is different (over/under) from the specified number.

This feature makes it possible to check the count results in various cases, for example, “difference from the specified number at only one end (front or rear) of the bundle,” “same differences from the specified number at both ends,” “different differences from the speci-

fied number at the two ends,” etc., and allows the operator to check for conditions such as differences from the specified number of bars in a bundle, mistakenly mixed short bars with different dimensions, misalignment of the bundle ends, badly-shaped steel bars, bundles containing misshapen steel bars, etc. from the result display screens shown in Fig. 10 and Fig. 11.

## 5. Conclusion

Application of AI achieved dramatic improvements in the performance of the deformed steel bar counting machine, including improvement of the accuracy of counts of steel bars in bundles and improvement of the discovery rate of badly-shaped steel bars and short bars. Although 5 years have passed since the device was put into operation, it is continuing to perform satisfactorily, contributing to ensuring product quality in the operations of customers and reducing the workload of operators. JFE Plant Engineering Co., Ltd. is engaged in further development and sale of high-accuracy counting and weighing machines and systems based on the experience gained in this development. In the future, we will continue to provide the optimum solutions for the problems faced by customers.

## References

1) Okazaki, T.; Sashida, T.; Okuno, K.; Tachi, K. Development of

- Automated Visual Inspection Technology Using Deep Learning. KONICA MINOLTA Technol. Rep. 2022, vol. 19, p. 97–102.
- 2) Aoshima, K.; Kawamura, S.; Nakano, S.; Nakamura, H. Study on Variant Extraction of Concrete Structures Using Image Recognition by Deep Learning. *Journal of Japan Society of Civil Engineers, Ser. E2 (Materials and Concrete Structures)*. 2018, vol. 74, no. 4, p. 293–305.
- 3) Ogata, T. The concepts of the Motion Learning of Robots with Deep Predictive Learning. *Artificial Intelligence*. 2020, vol. 35, no. 1, p. 12–17.
- 4) Watanabe, N.; Takago, R.; Suzuki, M.; Hadama, S. AI Utilized Dam Optimal Operation System. *JFE Technical Report*. 2023, no. 29, p. 28–33
- 5) Okatani, T. Research Trend in Deep Learning for Visual Recognition—Advances of Convolutional Neural Networks and Their Use—. *Artificial Intelligence*. 2016, vol. 31 no. 2, p. 169–179.
- 6) Ioffe, S.; Szegedy, C. Batch normalization: accelerating deep network training by reducing internal covariate shift. *ICML’15: Proceedings of the 32nd International Conference on International Conference on Machine Learning*. 06 July 2015, vol. 37, p. 448–456.
- 7) Nair, V.; Hinton, G.E. Rectified Linear Units Improve Restricted Boltzmann machines. *ICML’10: Proceedings of the 27th International Conference on International Conference on Machine Learning*. 21 June 2010, p. 807–814.
- 8) Ronneberger, O.; Fischer, P.; Brox, T. U-net: Convolutional Networks for Biomedical Image Segmentation. *International Conference on Medical Image Computing and Computer-Assisted Intervention*. 18 November 2015, Conference paper, p. 234–241.
- 9) Matsuoka, R. High Dynamic Range Image Processing. *Artificial Intelligence*. 2021, vol. 36 no. 1, p. 90–96.
- 10) Mann, S.; Picard, R. W. On being ‘undigital’ with Digital cameras: extending dynamic range by combining differently exposed pictures. *Proceedings of IS&T 46th annual conference (May 1995)*, p. 422–428.