EVALUATING THE PERFORMANCE OF AI FOR SORTING GREEN SOYBEAN

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Abstract
Almost all farmers who cultivate green soybeans do sorting manually, with a work efficiency of 12kg/h. They desire a sorting machine for green soybeans. In recent years, the performance of AI (artificial intelligence) has been improving because of deep learning. If we can use the AI for sorting by deep learning and mount on sorting machine, it will be possible to develop a high performance sorting machine. In this study, we made an AI to detect the green soybeans' position and judge its quality, and discuss how to make a high-performance AI. Results indicated that it is necessary to prepare both non-defective product and defective product image data when we make AI for sorting. It was found that when many quality characteristics were set and images of two or more varieties were mixed in the dataset, the performance of AI was low.

Key words: *AI; deep learning; YOLOv3; sorting; labor saving.*

INTRODUCTION
In Japan, green soybean is cultivated in many areas. For the past 10 years, the cultivated acreage of green soybean changed little, but the production of green soybean decreased. One of the reason is the sorting which people do manually. The work efficiency is 12kg/h, so many farmers desire a sorting machine for green soybeans. *Katahira, et al. (2011)* made a sorting machine of green soybean on a trial basis, but due to the structure of the detection unit, there were problems in sorting accuracy. In recent years, the performance of AI is improving because of the deep learning, and various research has been conducted to apply AI to the field of agriculture. In addition, the performance of the object detection algorithm is also evolving. Famous object detection algorithms include "Faster R-CNN", "SSD" and "YOLO". If we use AI which is made by using deep learning and the object detection algorithm, we may be able to develop the green soybean sorting machine with high performance and simple structure and save labor in selection work. As a first step to realize this, we must establish a method to make a high-performance AI to sort green soybean quality. The aim of this study was to determine the important elements necessary for making a high-performance AI for sorting green soybean using deep learning.

MATERIALS AND METHODS
(1) Green soybean image collection
The green soybeans used for image data collection were cultivated in the farm of Yamagata University in 2018. We collected the green soybeans' images to use a green soybean's prototype selector (PITA-EDS-mini01, PITA-EDS001, Gaochao Engineering Co. Ltd.). After collecting the images, they were cut into a square of about 250pixels, with one green soybean in each image. Finally the images were rotated in eight directions and to increase the number of pictures.
(2) Dataset preparation
We classified green soybeans by eight quality characteristics (Fig.1). Non-defective product is only "Good" and other seven are defective products. Before doing deep learning, we needed to create teacher data. It is the information about the quality of green soybeans in the image. Therefore, I used the software "LabelImg" and annotated. To investigate how difference in dataset size and composition affect the performance of AI, four datasets were prepared and four types of AI were built (Tab.1).
(3) Development AI by deep learning
The environment of the computer which we used for the deep learning is shown in Tab. 2. We used Darknet (Open Source Neural Networks in C language) as a framework for deep learning and YOLOv3 as an object detection algorithm. Darknet and YOLOv3 were developed in 2018, and they are one of the highest performance framework and object detection algorithm as of 2018 *(Joseph & Ali, 2018)*. The number of times of deep learning is three pattern of 10000 times, 30000 times, and 50000 times. In Total, twelve AIs were made.

(4) Evaluation of AI's performance

First we prepared 20 image datasets of the eight quality items and show to them each AI. Then we counted the number of image data that AI correctly judged the quality of green soybeans. The detection rate was calculated by the equation (1).

$$A = \frac{W}{20} \cdot 100 \quad (1)$$

Where A is the detection rate (%), and *W* is the number of image data that AI correctly judged the quality of green soybeans. Since the datasets A and B (Tab.1) did not include the image data of the quality characteristics of "Good", the AIs of the datasets A and B cannot detect "Good" green soybeans. So we recorded only the detection rates of the seven quality characteristics other than "Good" when we used the AIs made with datasets A and B to get the detection rate data. After that, we summed up the detection rates and divided by the number of quality items to calculate the average detection rate. We collected 5 iterations of the average detection rate data.

Next we selected the AIs with the highest average detection rate in each datasets and showed the AIs the "Non-defective product" and "Defective product" image data which was newly prepared. The "Non-defective product" image dataset included the images of only one quality characteristics of "Good", and the "Defective product" image dataset included the images of seven quality items of defective products. The "Non-defective product" and "Defective product" image dataset contain 25 images respectively. The sorting rate was calculated by the equation (2).

$$\eta = \frac{Wg}{25} + \frac{Wf}{25} - 1 \quad (2)$$

Where η is the sorting rate, and *Wg* is the number of image data that the AIs correctly detected a non-defective item when we showed the AIs the "Non-defective product" image data, *Wf* is the number of image data that the AIs correctly detected defective item when we showed the AIs the "Defective product" image data. If the AIs in datasets A and B did not detect anything when they saw the "Non-defective product" image data, we presumed that they could detect "Non-defective product". We collected 10 iterations of the sorting rate data.

(5) Data analysis

Statistical analysis was performed using SAS (ver.9.4; SAS Institute Japan, Tokyo). The Average detection rate and the sorting rate was analyzed by Tukey's test at 0.05 probability level.

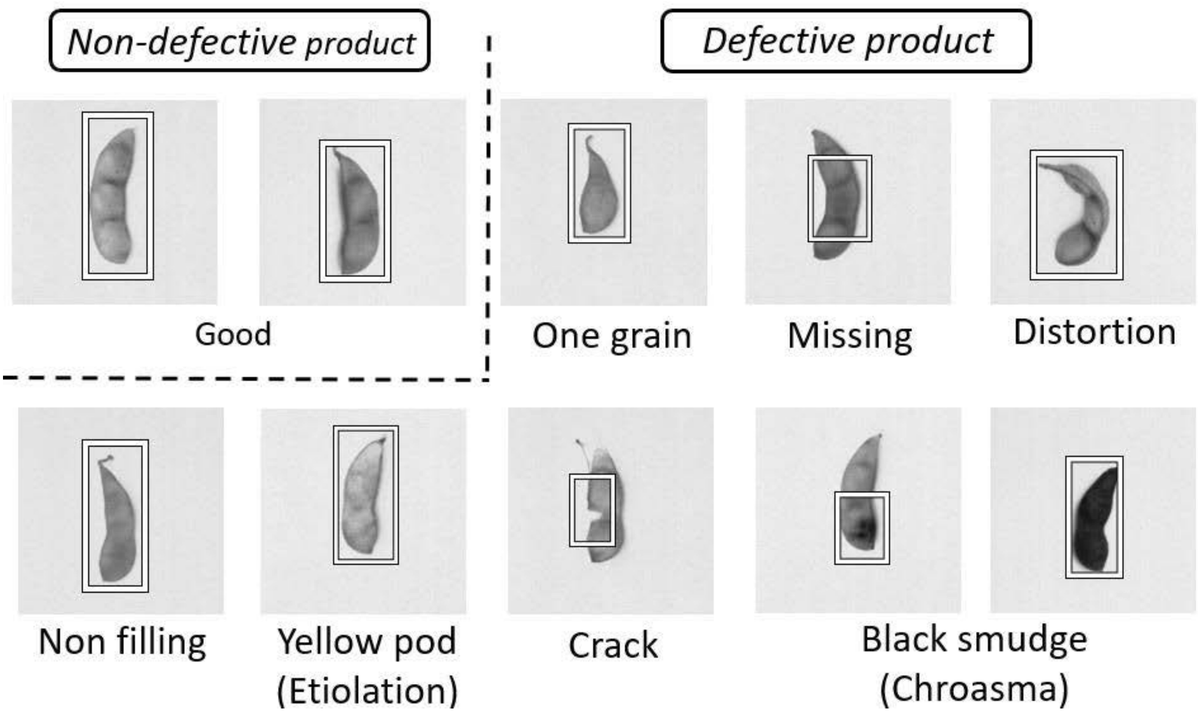

Fig.1 Eight quality items and area of annotation

Tab.1 Content of each dataset

Dataset	Content of data set	The number of image data	Variety of green soybean
A	7 defective characteristics excluding "Good"	1000 image data for each characteristic (total:7000)	Shonai-sango
B	7 defective characteristics excluding "Good"	2000 image data for each characteristic (total:14000)	Shonai-sango, Hiden
C	8 quality characteristics including "Good"	1000 image data for each characteristic (total:8000)	Shonai-sango
D	8 quality characteristics including "Good"	2000 image data for each characteristic (total:16000)	Shonai-sango, Hiden

Tab.2 AI development environment

OS	CPU	GPU	NVIDIA Driver	CUDA	cuDNN	OpenCV
Ubuntu 16.04LTS	Intel Core i7-4790S	NVIDIA GeForce GTX1080Ti (11GB)	410.72	10.0	7.4.1	3.4.0

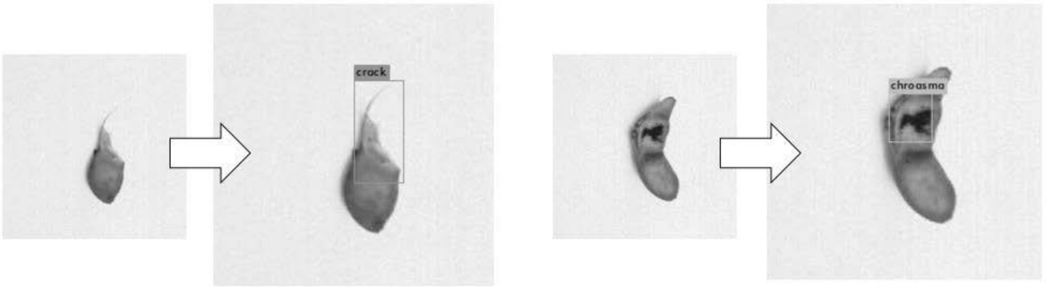

Fig.2 Example of quality judgement and position detection by AI

RESULTS AND DISCUSSION

(1) The average detection rate

The result of the average detection rate by each AI is shown in Fig.3. The average detection rate was highest for the AI of dataset B with 50000 times of deep learning, and the value was 88.6%. On the other hand, the average detection rate was lowest for the AI of dataset D with 50000 times of deep learning, and the value was 43.9%. There was no case that the AI could not detect green soybean at all. The datasets C and D included the “Good” images, so the AIs of datasets C and D have one more quality characteristic to detect compared to the AIs of datasets A and B. Further, the dataset D included the images of two green soybeans’ varieties. The shape and color of “Shonai-sango” and “Hiden” are not very similar. In particular, the shape and color of these two varieties of “Good” differ greatly (Fig.4). If there are many quality characteristics that we want AI to detect, with mixed varieties that are not similar in shape and color in the dataset, the performance of AI will be degraded.

(2) The sorting rate

The result of the sorting rate by each AI is shown in Fig.5. The average sorting rate was highest for the AI of dataset C, and the value was 0.59. On the other hand, the sorting detection rate was lowest for the AI of dataset B, and the value was 0.02. Compared to the AIs of the datasets C and D, the AIs of the datasets A and B erroneously detected a non-defective product as a defective product in many cases. This caused the low sorting rate of the AIs from the datasets A and B. This suggested that it is necessary to add the “Good” image data in the dataset when we developing the AI for sorting.

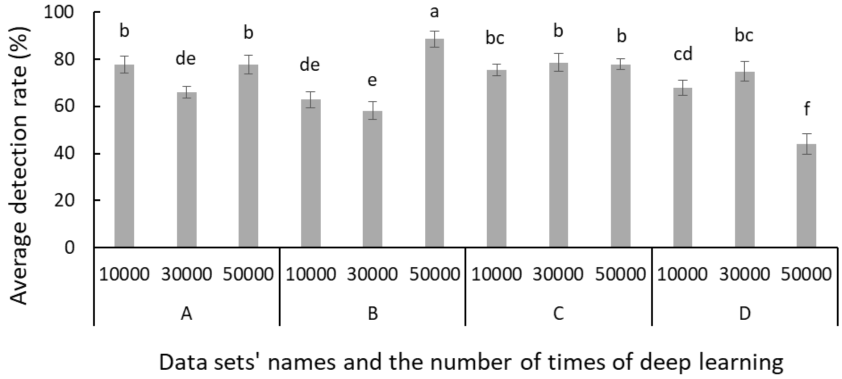

Fig. 3 Average detection rate

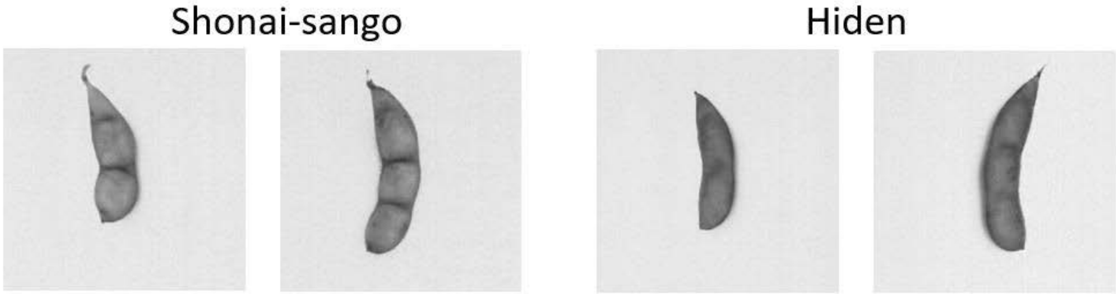

Fig.4 Example of “Shonai-sango” and “Hiden” Non-defective product image data

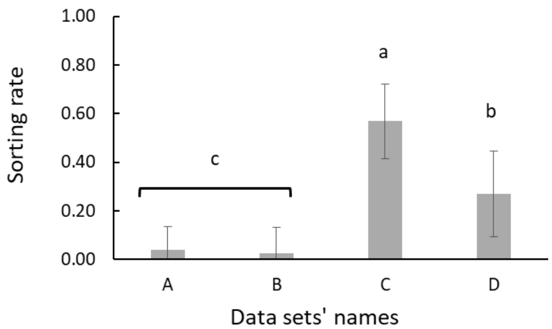

Fig.5 Sorting rate

In the past survey on green soybean sorting, in the case of manual sorting, the result of sorting rate was 0.59. From this, it was found that the sorting ability of AI with the highest performance is equivalent to that of humans.

CONCLUSIONS

This study sought to develop a sorting AI for green soybean that can be mounted on a sorting machine and it was shown that the AI can detect the green soybeans’ quality characteristics by looking at the appearance of them. Through this experiment, we determined the elements necessary for developing a high-performance AI. As computer vision technology is evolving every day, we will explore the use of other frameworks and object detection algorithms, and compare the performance of those AIs. In the near future we will be able to develop higher-performance AI and mount on a sorting machine. Finally, the findings from this study will be also useful in developing the AI for other crop sorting and other uses.

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