Vision-based Grade Classification of Green Soybeans Based on JA (Japanese Agriculture) Standards

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Abstract

Japanese agriculture is currently suffering from a shortage of young people and overwork. In particular, green soybean-grade sorting is an area where there is a high possibility of implementing AI technology. In this research, we proposed a method of data collection that contains green soybeans captured from top and side angles. With the custom dataset, we enhanced the AI model performance of judging grades with greater overall accuracy on most green soybean grade classes than in previous studies. The performance of the test dataset results across datasets achieved an accuracy of 0.93%. The performance of the AI model for top and side angle data were 92% and 97% respectively. The AI model was able to predict the grades of green soybeans from side angle view with higher accuracy compared to top-angle data. Although there are still misclassifications for some classes, Our proposed method showed adequate good performance overall for real-life implementation. This research can facilitate solutions to these problems facing Japanese agriculture.

Keywords: computer vision, green soybeans, vegetable quality Japanese cooperative(JA), object detection,

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1. Introduction

Overview

vegetables are biological products, they all grow differently in shape, size, and color even though they are cultivated in the same field. A lot of irregular-looking vegetables come out from harvests every year. In Japan, vegetables are sorted into grades based on the standards JA (Japanese Agriculture Cooperative) has defined, considering many elements including shape, damage, color, even size and weight before being sent to marketing places such as supermarkets and retailers. In recent years, consumption of green soybeans has increased due to health consciousness and the global popularity of Japanese food. This increase in consumption and problems with the elderly population are expected to result in a shortage of workers in Japanese agriculture. Therefore, This study is going to automate the sorting task using deep learning techniques and specifically focus on green soybeans. In this section, it will explain the background and motivation of this study.

The rest of this section provides general guidance for the preparation of a thesis.

1.1 About JA and their functions

Agricultural cooperatives, commonly known as JAs, are cooperatives organized by farmers throughout Japan according to Odaka [1]. Established under the Agricultural Cooperative Law, the main purpose of JA is to support and improve the livelihood of farmers. This support includes a wide range of activities such as providing agricultural advice, jointly purchasing materials necessary for farming at the lowest possible cost, and promoting the distribution and sale of agricultural products. To ensure the quality of vegetables in Japan, JA requires farmers to assign quality grades to each kind of vegetable before shipping it to marketplaces.Figure 1 shows images of green soybeans of each grade. The evaluation of quality grades differs depending on the prefectures. Tables 1and 2 show the evaluation of green soybean's grade in Niigata Prefecture and Miyazaki Prefecture, respectively. Niigata Prefecture's JA has stricter standards than the evaluation standard in

Miyazaki Prefecture, and green soybeans that are discolored, cracked, or irregularly shaped are graded as unsalable and are excluded from sale. This sorting task is worthwhile to mitigate the unsold food stock problem and put the right price on green soybeans based on their quality. Furthermore, JA contributes to the introduction of advanced agricultural technologies and methods to improve the efficiency of agricultural operations. JA not only innovates in agriculture but also optimizes farmers' work processes, protecting and enhancing their farming operations and livelihoods. Therefore, this study can be cooperated with JA.

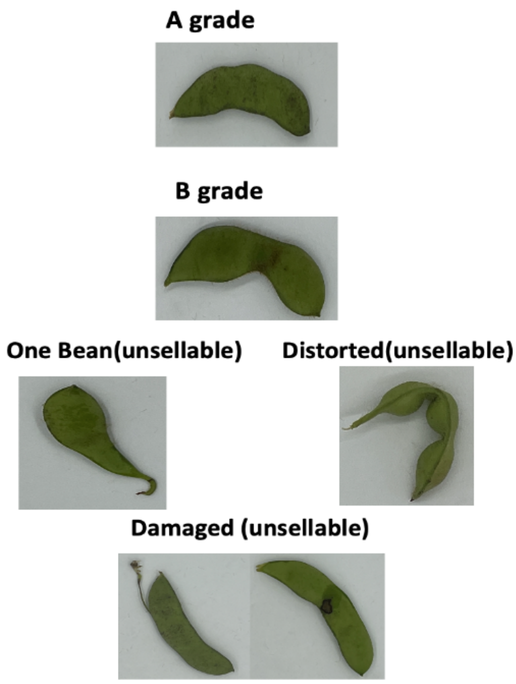


Figure 1: sample green soybean images of each grade

Table 1: JA grade evaluation table in Miyazaki Prefecture

A_grade	B_grade
1. The pod must have great shape, color, and more than two beans. 2. The pod must not be discolored, cracked, or diseased. 3. The color of the pod should be green	1. Two-three pods with one bean missing 2. The pod has no noticeable disease, insect damage, injury, or rot.

Table 2: JA grade evaluation table in Nigata Prefecture

A grade	B grade	Unselleable grade
1. The pod must have great shape, color, and more than two beans. 2. The pod must not be discolored, cracked, or diseased.	1. Two-three pods with one bean missing 2. The pod must not be discolored, cracked, or diseased.	3. The pod has insect damage, cracks, and distorted shapes.

1.2 Problem in Japanese agriculture

Meanwhile, most farmers in Japan are facing an overwork issue every year. This is because they are carrying the sorting task out manually by their hands. In the peak season, it is estimated that farmers spend 8 hours on the sorting task every day. To make matters worse, there is a serious social issue with a low birthrate and aging society in Japan. Nagatada [2] investigated the labor wages and profit distribution situation in the Ishiyama farming community by age group and reported that 32.4% of the total costs were spent on labor wages and that most of the part-time farmers were elderly, mostly over the age of 40. Additionally, including part-time workers, there were less than 10% of workers in their 20s and 30s in that region. They raised the issue about the shortage of young laborers in Japanese agriculture. As time goes by, it is estimated that the issue will become worse in the future. We suppose that it is necessary to automate agricultural works to reduce their overwork.

1.3 Volume of green soybeans produced In Japan

Japanese farmers are still sorting soybeans into grades manually by hand. In this section, we will show the annual volume of green soybeans produced in Japan. Green soybean known as edamame has long been a popular snack and side dish in Japan and has recently attracted attention as a health food for dieting and muscle training, and its consumption is increasing. Furthermore, with the growing popularity of Japanese food around the world, edamame is now widely eaten internationally. According to the Ministry of agriculture in Japan, 2020 [3], total edamame production in Japan was 65,200 tons. Of the total production amount l, Hokkaido Prefecture had the highest production, recording 8,820 tons. This was followed by Gunma Prefecture with 7,140 tons and Chiba Prefecture with 5,800 tons. Such a big volume of green soybean production poses a problem for Japanese farmers who continue to rely on manual sorting methods. Sorting green soybeans for grades based on JA is a task that imposes significant time and effort. This Japanese agricultural problem is recognized that it needs urgent development that AI replaces human work in agriculture.

1.4 The current methods for for vegetable sorting

Vegetable quality assessment with a vision-based approach has been researched by many for decades. Nagata&Cao [4] are pioneers who attempted to assess vegetable grades based on JA standards using a traditional neural network (multiple-valued neural network). Okuda [5] proposed a benchmark for the curvature of standard and distorted green soybean pods. Uchimura et al., [6] sought to classify cabbage into two classes; commercial use and raw consumption. A study conducted by Mori [7] specifically graded edamame using an object detection YOLO model, similar to this study. Moreover, there are some studies that assess vegetable quality with their subjective standards. Nurrani et al., [8] presented a CNN architecture that achieved better results by replacing the last classification layer of the CNN structure with a Support Vector Machine (SVM) instead of a fully-connected layer. Kumar&Shivani [9] proposed a vision transfer method to evaluate fruit quality. It achieved superior results compared to other CNN models they tested.

1.5 The process of shipping to market places

The process of green soybean harvest is followed by these steps as shown in Figure 2. It starts with the seeding process, and seeding is done with a tractor. Then, about three days after the seeds are sown, they begin to sprout, followed by the blooming of flowers. Eventually, pods appear, and seeds grow inside the pods. When the pods swell, they are considered unsalable as edamame and are harvested before they become soybeans. The harvested green soybeans are placed in a huller machine to eliminate leaves and trash. Then comes the grade sorting process. This process is to separate green soybeans between A_grade, B_grade, and unsalable grade following JA standards. Farmers are still doing this task on a conveyor belt manually by their judging and hand. The goal of our research is to automate this grade sorting process using deep learning techniques.

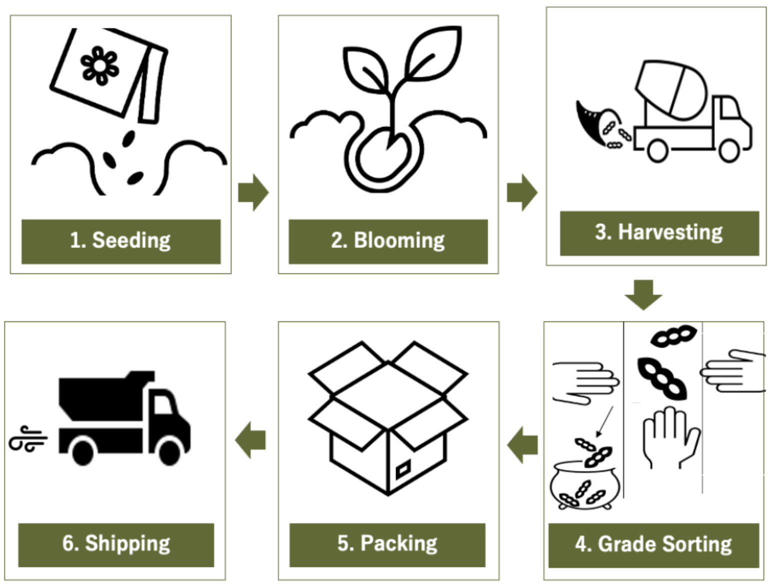


Figure 2: illustration for processes of shipping to market place

1.6 The importance of sorting vegetables

As mentioned earlier, 65,200 tons of green soybeans were harvested throughout Japan in 2022, and 52,200 tons of green soybeans among the total production was shipped to marketing places. 20% of harvested green soybeans were categorized as unsaleable grade. This means that defective green soybeans are frequently seen and sorted at actual sorting sites. This sorting task is carried out in order to prevent food loss. Without the sorting task, unusually shaped vegetables are likely to be unsold stock which will lead to food loss eventually. Those usually-shaped vegetables go to processing. In this way, they've been able to deliver vegetables that look as perfect as possible to the supermarket. Jaeger et al., [10] researching if quality perceptions regarding fruit's appearance influence customers rejecting consumption, has mentioned that fruit's defects of rot and skin cut were associated with rejecting consumption the most. Therefore, rather than selling all vegetables at the market, separating vegetables into those that can be sold and those that cannot be sold leads to a solution to food waste.

1.7 Research Purpose

As the technology developed, agricultural work has been mechanized significantly especially from seeding to harvesting. For example, Motoki&Yuyama [11] conducted an experiment comparing the efficiency of automated machinery and manual labor in transplant cultivation and reported that work could be done up to four times faster with machinery. However, the sorting task still has been done manually. The efficiency of this sorting task can be considerably improved by mechanizing the process with AI computer vision techniques. Thus, the implementation of AI is required. In this study, we focused on developing software that grades and classifies green soybeans' appearance based on JA's standard.

1.8 Thesis Overview

1.8.1 Research Contributions

This research has accomplished the following contributions:

- Further developed a green soybean dataset based on JA's standards.
- Proposed an improved experimental setup for judgment of green soybean's grade based on JA standards.
- The YOLO model trained on the original data set demonstrated that it can perform with higher accuracy and speed than human work.

1.8.2 Thesis Structure

This thesis is organized as follows: Chapter 2 talks about the thesis's foundation on multiple approaches based on computer vision to vegetable quality classification. Chapter 3 details the experimental setup for this study. Chapter 4 analyzes the results of the experiment. Finally, Chapter 5 discusses limitations and opportunities for future work.

2. Literature Review

The vegetable sorting task is so fatiguing for farmers all around the world. To relieve their burdens for the task, there are so many related works on assessing the quality of vegetables, although most were not evaluating the quality based on the national standards. Few research papers have worked on classifying vegetable grades based on JA standards, and even fewer papers sorting specifically green soybeans. To automate this, technologies like Image Processing, Object Detection, and Image Classification Models using Deep Learning have been studied to implement. Image Processing enhances digital images for feature identification like size and color. Classification Models categorize images by analyzing their characteristics like color uniformity and size. Lastly, Object Detection recognizes and finds the location of objects in images. Lastly, these technologies collectively automate and refine the vegetable sorting process, aligning closely with national quality standards. The most current and similar paper Mori [7] experimented with sorting green soybeans in grades based on JA standards using deep learning methods. They compared the performance of image classification and object detection models in the task. The performance of the Object detection model showed a greater result than the image classification model.

2.1 Image classification-based vegetable quality assessment

Nagata & Cao [4] studied on grade judgment of strawberries and papers based on JA standards using machine vision. Their study is not only classifying into grades but also size as well. In the study), they used a traditional neural network (multiple-valued neural network) by feeding data on the widths and heights of various positions of the input vegetables. The limitation of this study is that it always needs human support because they have to manually measure and put input values into the neural network. Uchimura et al., [6] trained traditional CNN models with cabbage datasets to classify them into two classes: commercial use and raw consumption. They collected a dataset by taking pictures of cabbages inside a photo box with an LED light. Overall, their score of the research reached 0.89, however, the processing speed was 5.8 seconds, which is too slow for sorting tasks in real life. We believe by using the latest cnn based model the speed issue could have been solved. Kumar et al., [12] proposed a CNN architecture that can classify kinds of vegetables and their quality assessment. It attained 98% accuracy for test data images, and 0.0076 seconds per image for processing speed. However, I assume that the accuracy would be decreased if the task becomes more complex than just categorizing “fresh” and “rotten”. Sustika et al., [13] have also explored five CNN models’ performances on strawberry quality inspection. It ranks strawberries into 4 grades, scaling from 1 to 4. However, their project reached around 85% and required big memories for the inspecting task, as it was not a simple task.

While CNN-based image classification models have the potential to classify vegetables for simple tasks that merely classify them as ”good” or ”bad,” they still have some problems with tasks that require a more detailed inspection of the vegetable’s appearance.

2.2 Image processing based vegetable quality assessment

OKUDA et al., [5] provided a good method to classify between curved green soybeans and standard-shaped green soybeans measurably. They use a centroid radius with peak adjustment and measure the length between the stem and tip of the soybean to classify between normal, one-bean, deformed shaped soybeans. For the experiment of classifying between standard and curved-shaped soybeans, they measure three points: long-axis center line ratio, short-axis center line displacement ratio, and centroid displacement. They compared those three ratios to see which element has shown differently between these the most. They found that the difference between the minimum and maximum centroid displacement was largest among other parameters. This method could identify distorted soybeans with 100% accuracy in their study. However, other defects such as discoloration and cracks were not covered, relying on human support to measure these key points. If only an algorithm or computer vision technique could measure those points, this method would be a good point to start to improve our method in the future. In the data preprocessing process, Uchimura et al., [6] removed noise and unnecessary background information in the image data by applying a traditional image processing technique. They binarized the image color with 85 threshold values. If the pixel of an area is smaller than 1000 pixels, they change the area to black. Shiraishi & Takeda [14] proposed a system for inspecting the whole surface of vegetables from 6 angles. The system detected three elements; size, shape, and bruise. After capturing an image of the target vegetables, it converts from RGB color space to L*a*b color space. For size measurement, it counts the number of pixels of the extracted target area. As for shape detection, it surrounds the extracted target area with a rectangle bounding box and calculates the ratio of its short and long axis. Lastly, it applies the morphological operation to extract the bruises on the target object. While their classification experiments have achieved 90% for detecting size and bruise, they struggled to classify good and bad shapes with 65% accuracy. Only putting an approximated rectangle box on the target vegetable was not enough to detect various types of deformed vegetables.

In general, these image-processing approaches are good at finding specific types of features but always have limitations in detecting features over a wide range of areas. Thus, nonetheless depending only on image processing approaches is not practical in real-life sorting situations, these techniques have the potential abilities to be a nice complement to improve the weakness of the proposed model.

2.3 vegetable's quality assessment with object detection model

Mukhiddinov&Muminov [15] uses the yolov4 model for multi class fruit and vegetable categorization and classifying into fresh or rotten. Furthermore, They enhanced the yolov4 model's performance from 50.4% to 75.8% by applying the mish activation function in the backbone step. As it was categorizing many kinds of vegetables, the performance of the enhanced version was only measured up to 75.8% accuracy. The processing time was faster than a second. Mori [7] got objection models and image classification models to classify green soybeans into grades based on JA's standards. They collected 7 different brands of green soybeans images and trained with several models. In the experiment, they compared the performance between yolov3 and faster-can. Scores of the both models were 0.79 and respectively, which is not accurate enough for the real workplace. The limitation of this study was that they struggled with detecting one of the features green soybeans have which significantly decreased their accuracy. The feature was the defects that the greenery appeared to contain beans inside its pod but did not have. This is because it is hard to detect the number of beans existing in the pod from only the top-angle view.

Obtained through previous research and their shortcomings, we established the environment for data collection and created our original dataset of green soybeans. By feeding green soybeans' side angle data into yolov8, we were able to greatly surpass the results of the earlier studies.

Previous research showed that while traditional image processing methods are applicable for detecting simple defects in vegetables, each method has certain defects in vegetables that it was weak at. Also, the processing speed was relatively slower than other deep learning methods. CNN-based image classification methods have proven to be able to detect a wide variety of defect kinds, but comparing their performance with that of humans, they have yet to show results that can replace humans in a real-life vegetable sorting workplace.

Whereas image classification models can be useful for this sorting task, it is primarily designed for only classifying images from the whole image information. Therefore, image classification models are usable only when the camera captures one object in the frame. On the other hand, object detection models such as Yolo were designed for detecting objects and their location in images. We believe that they are more suitable for this task, as it requires a robot picking soybeans up and moving them into the right box in a real-life sorting workplace.

3. Methodology

In this study, as shown in figure 3, our object detection model specifically focused on green soybeans. It provides a more feasible result to sort green soybeans based on JA standards than previous works. As illustrated in Figure [], the process of this experiment began with collecting green soybeans. Next, we photographed these green soybeans and annotated the images on Roboflow. Finally, we used the completed annotated dataset to train YOLO.

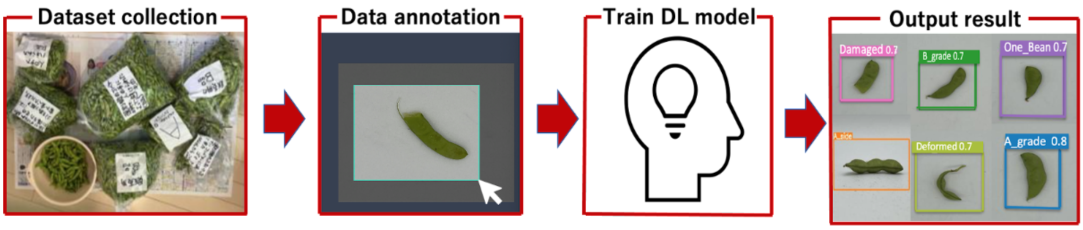


Figure 3: Steps of our methodology

3.1 Data collection

To create our original dataset for this study, we firstly collected green soybeans from Takai Farm (Niigata Prefecture). With Mr. Takai's cooperation, when the green soybean was delivered, they had already been sorted into grades such as A-grade, B-grade, and unsalable, each in separate bags. Our labeling method is not judged by our subjective view. The green soybeans data was taken with the iPhone 13 model. We shot those photos using a photography box(see Figure 4). This photo box is equipped with various features. It measures approximately W44 x H43.5 x D59 cm, allowing for photography from not only the front but also from the top for overhead shots, enabling shooting from various angles. Furthermore, the photo box is fitted with a USB-powered LED light with 35 bulbs, providing about 530 lumens. This LED lighting uniformly illuminates the inside of the box, allowing for the collection of images under consistent lighting and background conditions. This helps prevent accuracy issues due to environmental changes when implementing the AI edamame sorting machine in real-life scenarios. The images were captured with an aspect ratio of 1:1 (square), a size of 3024×3024 pixels, vertical and horizontal resolution 28.5%, auto exposure mode, flash off, and in JPEG format (see Table 3). In this experiment, to detect defects on the sides of the green soybeans, we took photographs from three angles (from the top and the side). The camera positioned above was 30 cm away from the green soybeans, while the side camera was at a distance of 20 cm. As for magnifications, the camera's top and to the side were set at x2.8 and x2.2, respectively. By setting up cameras and equipment on a belt conveyor as described above, enables to prevention the impact of irregular environmental changes such as weather and lights on the accuracy of AI predictions. By setting these shooting environments, we created a custom green soybeans dataset consisting of 4612 images.

Figure 4: Photobox image

Data Angle	Top	Side
Pixel height&width	3024 x 3024	3024 x 3024
Digital zoom ratio	3.0	2.2
Brightness value	7.3 ∼ 7.5	7.3 ∼ 7.5
Color model	RGB format	RGB format
Resolution	28.5%	28.5%
Explure mode	explure auto	explure auto
Flash	OFF, No fire	OFF, No fire
Focal length	5.1	5.1
Lens model	Phone 13 back dual wide camera 5.1mm f/1.6	Phone 13 back dual wide camera 5.1mm f/1.6

Table 3: Camera setting

3.2 JA Grade Evaluation

In this study, an object detection model(You Only Look Once) was used to classify green soybeans into 9 classes (see Figure 5). Before sending green soybeans to market places, they are sorted into grades according to the following criteria in Figure 5). Due to the numerous categories under JA's unsellable grade classification.

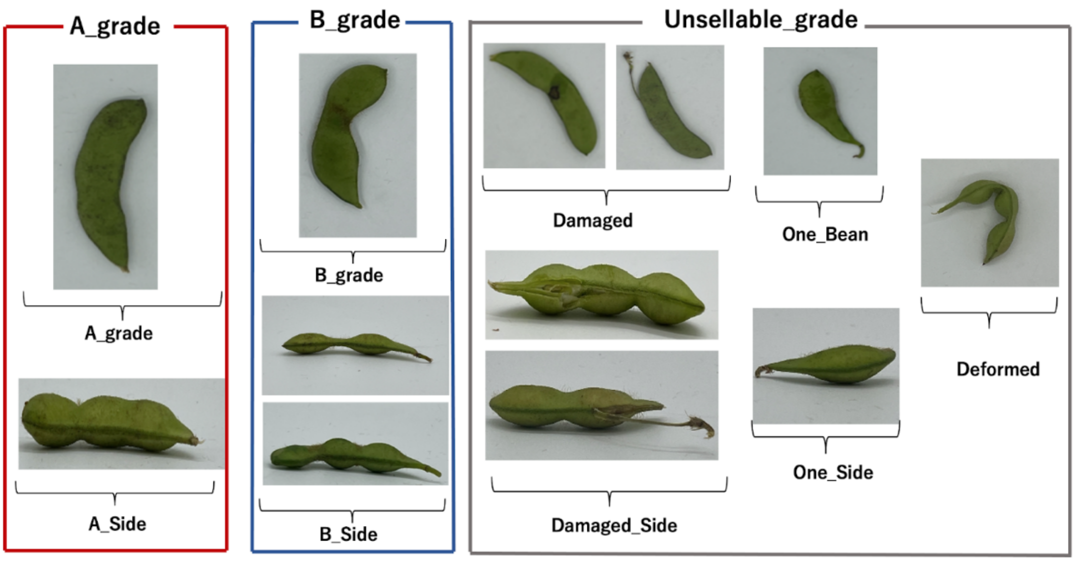
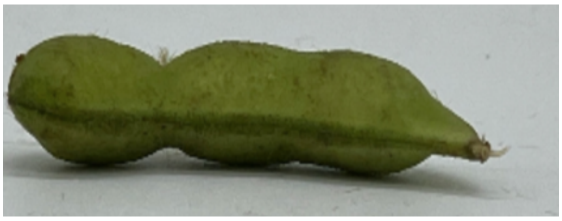


Figure 5: Green soybeans JA grades

3.2.1 A Grade Evaluation

Firstly, good quality (A-grade) green soybeans must have at least two beans inside the pod as shown in Figure 6a and 6b. Additionally, to be classified as A-grade, the green soybean should be free of dirt, insect damage, and deformities, and the pods should not be small or immature.

(a) A_grade



(b) A_side

3.2.2 B Grade Evaluation

B-grade green soybeans are considered to be of lower quality compared to A-grade, but they are still treated as goods of marketable quality. These B_grade green soybeans are circulated in the market, and are purchased by Japan Agricultural Cooperatives(JA) for about half the price of A_grade green soybeans.

There are two main characteristics of B_grade green soybeans. One is when there are spaces between the beans inside the pod, or when the beans are skinny as shown in Figure 7c. The other is when the pod is shaped to contain more than two beans, with a mixture of beans that are thick and those that are not, or in cases where the pod contains no beans at all (see Figure 7a. Many previous researchers Mori [7] have faced challenges in classifying these B_grade features the most, because, typically, humans find these features from touching, making it difficult for AI to distinguish these characteristics from only visual information of a top-angle view.


(a) B_grade sample image


(b) B_side sample image


(c) B_side sample image

Figure 7: B_grade soybeans with varying quality.

3.2.3 Unsaleable Grade evaluation

Unsaleable grade is a lower grade than any other grade in JA standard. As unsaleable grade green soybeans are so defective that nobody would buy them in the supermarket, they are usually sent to processing plants and processed into another product. In our study, we made three classes within the grade: damaged, one_bean, and deformed. later, we will provide detailed explanations of the characteristics of these classes

3.2.3.1 Characteristics of One_bean class

One_bean green soybeans refer to green soybean pods that contain only a single thick bean inside the pod (as shown Figure 8a). However, if a pod contains one thick bean and one extremely small bean, the extremely small bean is still counted as one bean. Therefore, such pods do not fall under the One_bean category.

(a) One_bean

(b) One_side

Figure 8: One_bean class soybeans data samples

3.2.3.2 Characteristics of damaged class

Damaged class green soybeans are pods that have dirt, insect damage 9a, cracks 9b, bursts 9c, or black spots, or are over-ripened and have turned yellow. Moreover, even within the Damaged class of green soybeans, when two or more classification elements are present, they are categorized according to the most prominent characteristic based on our subjective judgment.

(a) Insect damaged pod

(b) Cracked pod

(c) Burst pod

Figure 9: Damaged class soybeans data samples

3.2.3.3 Characteristics of deformed class

The deformed class green soybeans are pods that are misshapen, either bent or with two pods fused together. We put data taken from top and side angle altogether into one class.The reason is that when placed at the shoot spot, deformed green soybeans do not stand properly unlike other classes. Even if photographed from the top angle, the surface of these soybeans may not be captured, and the sides might be captured instead. Separating those green soybean images into top and side class could potentially confuse the AI if these side views are treated as top angle images. Therefore, we did not include images of deformed edamame taken from the side angle in the training dataset

Figure 10: Distorted pod

3.3 Annotation for training dataset

After collecting the image data, we annotated the image data for AI training. Annotation involves marking the area of the green soybeans in the image with a bounding box and assigning category labels to each green soybeans. We did the data annotation task in Roboflow, which is an online platform for developing, training, and deploying dataset and machine learning models. The annotation range is as shown in Figure 11, with bounding boxes encompassing the entire pod. There are 9 classification categories for annotation.

Table 4 shows the number of annotations and images in the training data. It was not possible to have an equal number of annotations for each classification category among the collected edamame, as the edamame with features of each category do not exist in equal numbers. Collecting data for the deformed class of edamame was particularly challenging. Therefore, the number of images for the deformed class of edamame is the smallest among all the classes

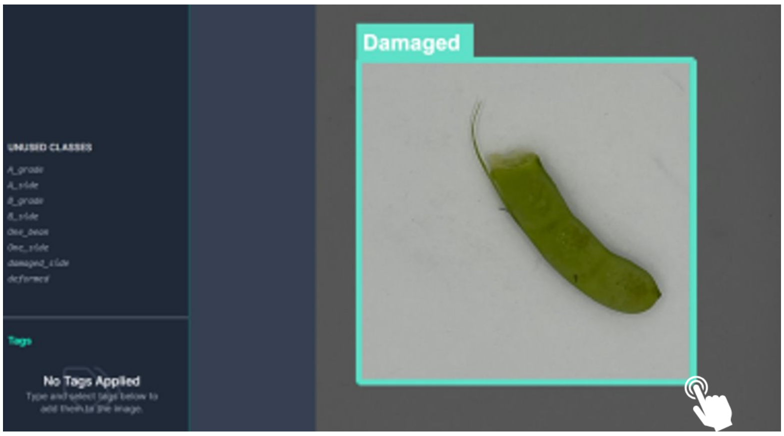


Figure 11: Data annotation process

class	the number of images
A_grade	779
A_side	598
B_grade	489
B_side	481
One_bean	447
One_side	388
Damaged	726
Damaged_side	551
Deformed	153

Table 4: The number of data images for each classes

3.4 Training process

In this study, we used Ultralytics YOLO (You Only Look Once) version 8 models to train our original custom dataset. Ultralytics is a software company that provides the open source code for using YOLOv8 they developed. In the experiment, I used Python 3.10.12 and torch-2.1.0+cu118 . torch-2.1.0+cu118 is a version of Pytorch which is an open-source machine learning library. As depicted in Figure 12, the dataset was partitioned into 60%, 30%, and 10% for training, validation, and test data, respectively. The hyperparameters for the Yolov8 training process were set as follows 5: the number of training iterations was 150, the image size was resized to 640x640 for the input layer size , the batch size was 64, and the optimizer was SDG with learning rate 0.01.The patience of training process is set to 50. The training epoch has automatically stopped to 145 epochs as the training accuracy did not improve for the next 50 epochs from epochs at 95. The training process was executed on Google Colab, leveraging the power of an A100 GPU. The choice of the A100 GPU was based on its high computational capabilities, making it well-suited for training deep learning models efficiently. T4 GPUs and V100 were also candidate GPUs for the training. However, the T4 GPU is less powerful than A100s, and V100 processing speed was slow. They were not sufficient enough for this training process., as it requires high complexity and memory. The training process was completed in 1.7 hours, while V100 and T4 took over 9 hours .

Figure 12: Dataset split

Ultryatics YOLOv8.0	torch-2.1.0+cu118
Epochs	150
Optimizer	SGD
Learning Rate	0.01
Weight	64
Patience	50
Batch	64
Image Size	640x640
Verbose	True

Table 5: Training hyperparameters

3.5 Data Augmentation

Data augmentation played a pivotal role in enhancing the model's ability to recognize soybeans in various scenarios. Augmentation techniques such as horizontal flipping, horizontal and vertical shearing (±15°), hue adjustment within a range of -9° to +9°, saturation modification within -25% to +25%, and brightness alterations within 0% to +25% were applied to diversify the training data. Horizontal flipping, horizontal and vertical shearing are used to train the model to classify correctly, even if the position of the camera or the orientation of the edamame within the captured frame is shifted. Moreover, In actual sorting environments, various factors such as different lighting conditions at the photo shoot spot and foggy weather can occur. Therefore, Hue and Saturation adjustments were applied. Also these can prevent the model from only relying on color for the classification. This data augmentation process helped the model become more robust by exposing it to a wider range of potential image variations.

3.6 Classification Report Evaluation

To investigate how accurately the Yolo model detects green soybeans and classifies them into nine discriminative components, the experiment evaluated performance by calculating F-scores from Precision and Recall. These are common metrics 6 for evaluating machine learning models and their performance in the computer science study field. They are derived from equations (1) through (3).

	Predicted	
	Positive	Negative
Actual	True Positive	False Negative
	False Positive	True Negative

Table 6: AI evaluation matrix

True Positive represents cases where the AI accurately detected and classified green soybeans in the test images. False Positive represents cases where the AI misclassified the category of green soybeans it detected. False Negative refers to cases where the AI failed to detect the green soybeans that should have been detected

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{1}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{2}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

Precision measures the accuracy of the AI in classifying detected green soybeans, with values closer to 1 indicating fewer misclassifications. Recall indicates how well the AI detects target green soybean, with values near 1 showing minimal misses. The F-score, a harmonic mean of precision and recall, reflects the AI's overall accuracy in detection and classification, with values closer to 1 being better

4. Result & Discussion

Overview

In this section, we will explore the results of the experiment. This section consists of four parts. Firstly, we will show the performance results such as classification reports, confusion matrices, training graphs, and quantitative results. Then, we will explain our analysis using the quantitative result and a table that compares the result between top and side angle data performance and findings. Lastly, we will discuss the cause of misclassification.

4.1 Classification report

The trained model was evaluated on the 692 test images that were not included in the training data. We evaluate the recognition performance in terms of precision, recall, and F1 score.

Classes	Precision	Recall	F1-score
All	0.94	0.93	0.93*
A_grade	0.92	0.92	0.92
A_side	0.98	0.94	0.94
B_grade	0.97	0.84	0.90
B_side	0.97	0.98	0.97
One_Bean	0.95	0.95	0.95
One_Side	0.98	1.0	0.99
Damaged	0.94	0.87	0.90
Damaged_side	0.90	0.98	0.94
Deformed	0.86	0.86	0.86*

Table 7: Result of green soybeans grade classification

The performance of the YOLOv8 model on the edamame dataset is summarized in the precision, recall, and F1-score as shown in table 7. The model shows strong precision and recall across all classes, achieving an F1 score of 0.93 in total. Notably, 'A_side', 'B_side', and 'One_Side' classes demonstrate superior precision and recall, resulting in high F1-scores of 0.94, 0.97, and 0.99 respectively. The 'Deformed' class, while having the lowest F1-score of 0.86, still indicates a reasonably good performance. The balanced precision and recall suggest that the model effectively recognizes and correctly classifies the majority of features in each class.

4.2 Confusion matrix

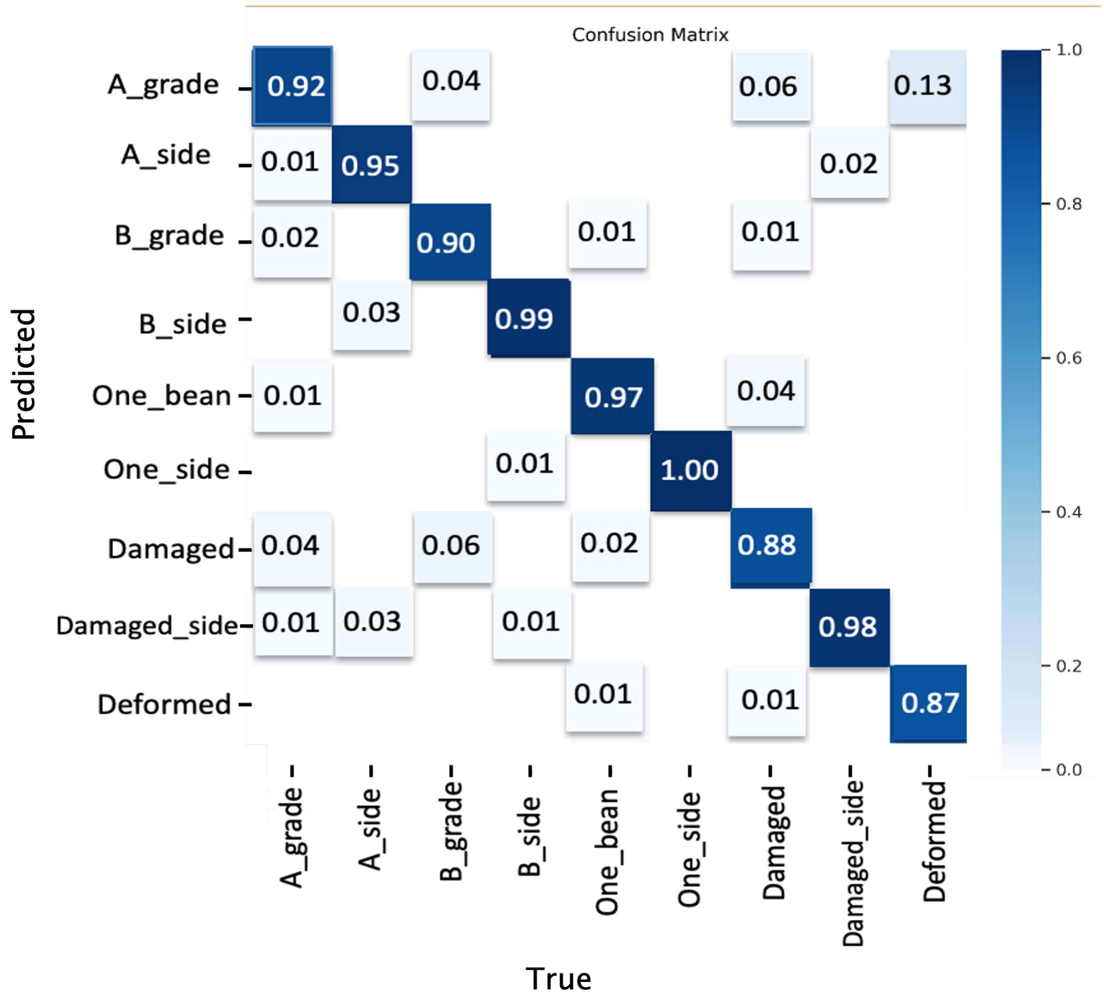


Figure 13: Result of the grade classification with Confusion Matrix

Figure 13 shows the confusion matrix of the model performance for test dataset performance. The 'B_side' and 'One_side' classes show almost 100% classification performance. The accuracy was generally over 90% and classifications were generally low, however deformed classes were often misclassified with A grade class. Also damaged class was frequently predicted as A_grade and B_grade.

4.3 Qualitative results

A_grade

Figure 14: A_grade results

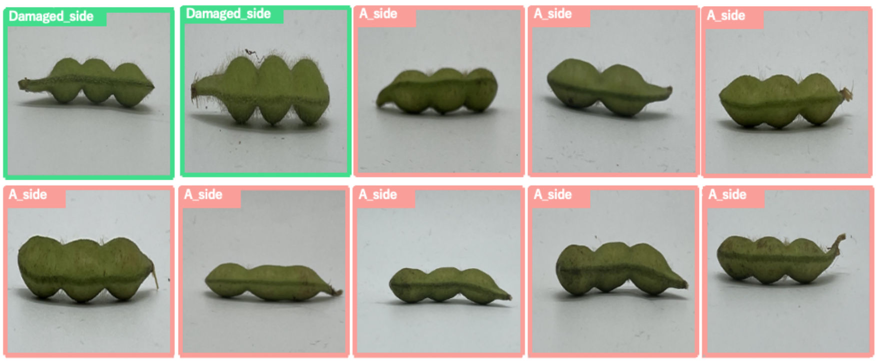


Figure 15: A_side results

B_grade

Figure 16: B_grade results

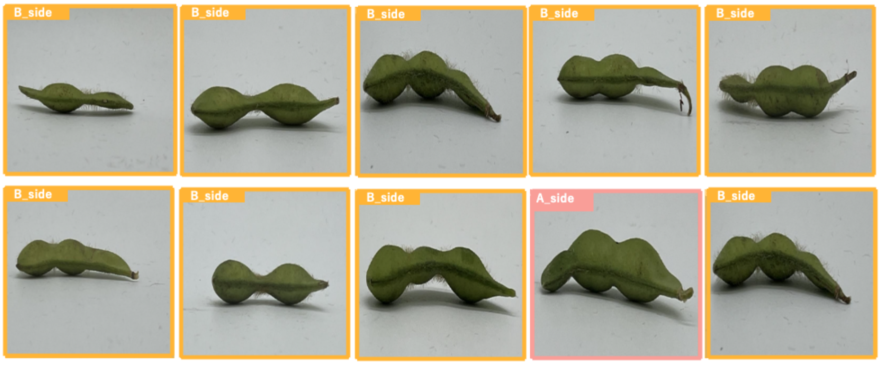


Figure 17: B_side results

One_bean class

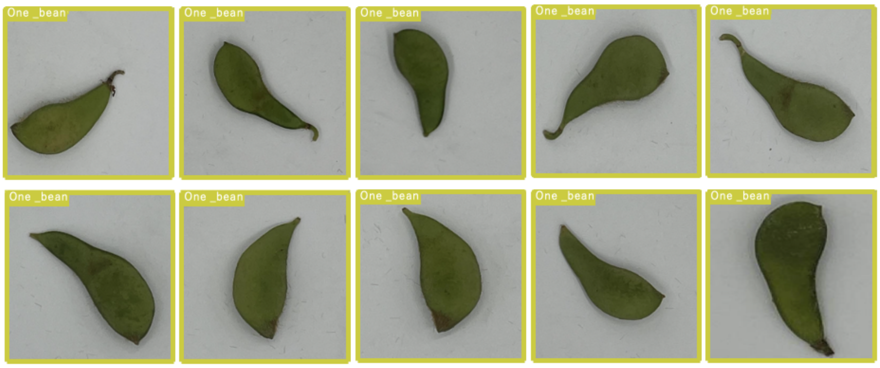


Figure 18: One_bean class results

Figure 19: One_side class results

Damaged class

Figure 20: Damaged class results

Figure 21: Damaged_side class results

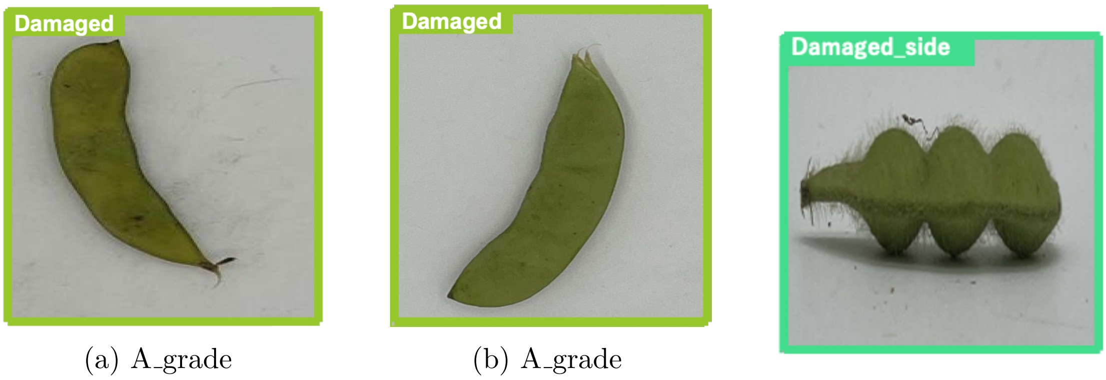
Deformed class

Figure 22: Deformed class results

4.4 Analysis of misclassifications

4.4.1 A_grade & A_side

The f1 scores for A_grade and A_side classes are 0.92 and 0.95 respectively, so there were relatively few misclassifications in these classes. Firstly, our model misclassified some A_grade green soybeans with the damaged class as Figure 23 shows. This is because those green soybeans have minuscule damaged class features. For instance, green soybean in Figure 23a has a microscopic black dot on its pod. As for Figure2 23b green soybean's pod have torn on its tip. One of the misclassification happened in A_side class was Figure 23c green soybean. Our model classified it as damaged_side class since there is a small trash onto the pod. Therefore, these results and misclassification indicate that the model can detect so small defects that Japanese farmers ignore



(a) A_grade misclassification

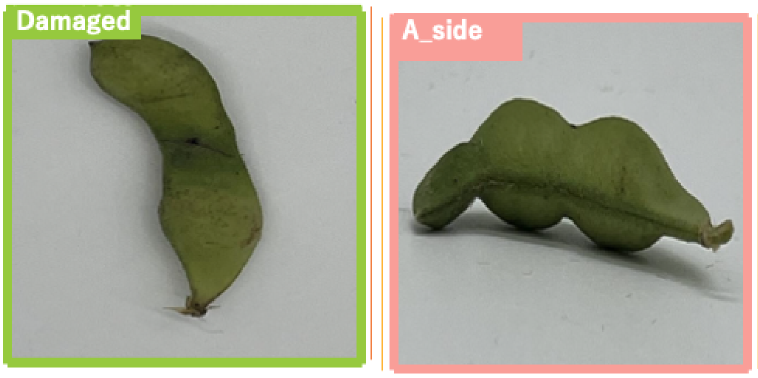
(b) A_grade misclassification

(c) A_side misclassification

Figure 23: A_grade classes misclassifications

4.4.2 B_grade & B_side

As for grade B green soybeans, F1-scores of these B_grade and B_side classes have achieved 0.90 and 0.99 respectively. There were paltry occurrences of misclassification in these classes (see Figure 24. Figure 24a is a misclassification case that happened for B_grade class. It took the green soybeans with damaged_class due to the same reason we explained in the previous class discussion. Figure 24b was miscategorized as A_side, due to the similarity between A_side and B_side features.



(a) B_grade misclassification

(b) B_side misclassification

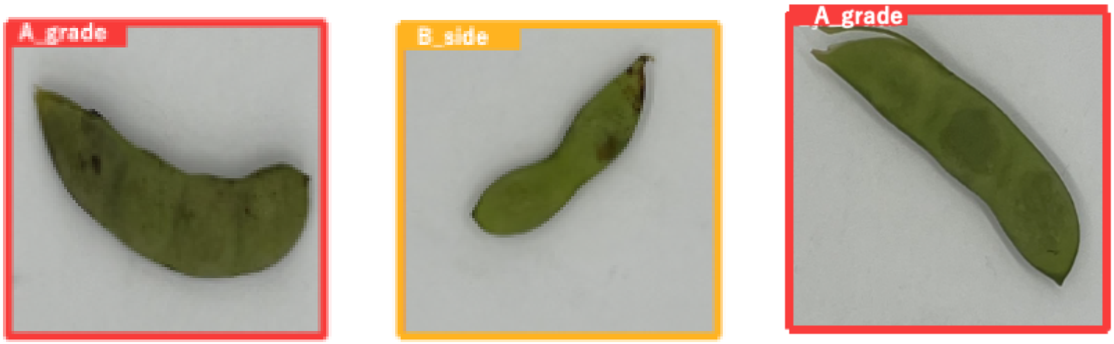
Figure 24: B_grade classes misclassifications

4.4.3 One_bean & One_side

In one_bean and one_side classes, misclassification did not happen owing to their high accuracy.

4.4.4 Damaged & Damaged_side

There was a large difference between the scores of the damaged class and the damaged_side class 25. Although the score of the damaged_side class was 0.98, which is extremely high compared to other classes, the damaged class had the lowest score of 0.9, second only to the deform class. The model was unable to discern any discoloration or splitting in these pods, as shown in figure 25a, 25b and 25c.

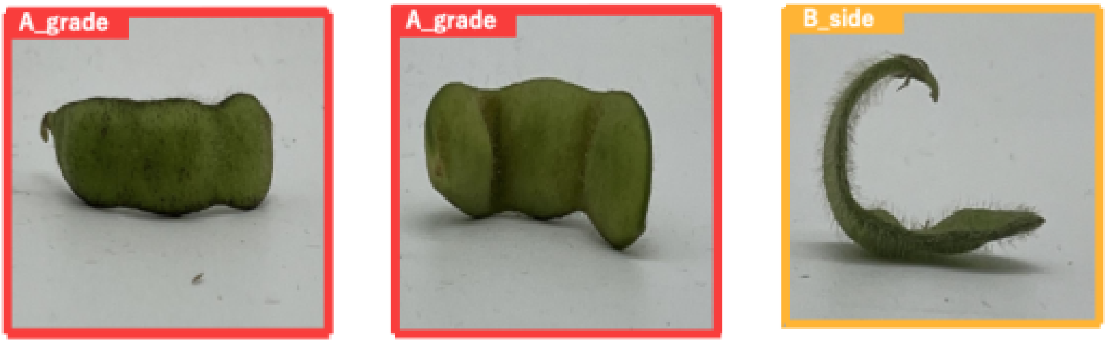


(a) damaged class result (b) damaged class result (c) damaged class result

Figure 25: Damaged classes misclassifications

4.4.5 Deformed class

Among all grade classes of green soybeans, the deformed green soybean class had particularly low F1 scores 0.86 compared to other classes reaching over 0.90. It was classifying deformed class green soybeans with A_grade. The most misclassified feature of the deformed class was distorted green soybeans with three thick beans in the pod like A_grade. Figure 26a and 26b are test images of deformed class with the characteristic. Green soybeans with this characteristic cannot stand in the camera's spot due to its shape, and the surface with characteristics of A-grade class is captured in the frame, so it is misclassified as A_grade. However, there were also some other misclassifications of deformed class characteristics, as shown in Figure 26c although this type of characteristic is relatively distinctive for the human eye compared to other class characteristics. Another possible reason for this misclassification is due to the shortage of deformed class data images.



(a) First image (b) Second image (c) Third image

Figure 26: Deformed class misclassifications

4.5 Analysis of the result between top and side angle data

Classes	Top Angle	Side Angle
Overall	0.92*	0.97*
A_grade	0.93	0.96
B_grade	0.90	0.98
One_Bean	0.95	0.99
Damaged	0.90	0.94

Table 8: F1 score comparative result

(a) challenging data sample (b) challenging data sample

Figure 27: Challenging data samples

Table 8 shows the F1 scores for the top and side angle classes, separated by column. The overall class F1 scores for the top and side angles were 0.92 and 0.97, respectively. Other side angle classes were also generally higher than the top angle classes. This happened because there are green soybean's feature that are easier to detect from side angle rather than top angle. For example, there is a B grade feature that the pod is missing beans or having a space between beans inside the pod shown in Figure 27a and 27b. These characteristics are difficult to detect from data from only the top angle. To detect these features using information from the top angle alone, the thickness of the bean and the bulge of the pod must be recognized, making it a very difficult task for the model to learn. The proposal of Mori [7] faced difficulties in accurately detecting these nuanced features. In addition, damages, discoloration, and tears in green soybeans are not always on the surface of the pod, they are on the side of the pod in some cases. Therefore, determining the grade of soybeans only based on the information from top angle view does not provide enough information to correctly classify the grade. Therefore, by feeding side angle data, we were able to enhance the model's ability to discern even minor characteristics, leading to improved classification performance.

5. Conclusion

Japanese agriculture in recent years has been facing issues of labor shortages and overwork. The cause of these problems are due to the delay in mechanization of Japanese agriculture and an aging and declining population. In this study, we focused on the automation of grading and sorting tasks in agriculture through AI, which is still predominantly done by hand, imposing heavy labor on farmers daily. Automating the green soybeans sorting task with AI will be a solution for the problems they face. This research contributes to improving the efficiency of green soybeans grade sorting tasks based on JA standards. In the process of dataset collection, green soybeans were photographed from top and side angle in a photobox which always allowed the data to be constantly captured in a light- and weather-independent environment. Then we trained an object detection model YOLOv8 with the custom dataset we created. The trained model with our custom green soybeans dataset showed promising results for implementation in the real-life grade sorting task on Japanese farms. It achieves a greater overall accuracy and score on most green soybeans grades than previous studies. Although there are still misclassifications for some classes. By analyzing the result of testing, it was found that feeding side angle information for the training model enhances the model's capacity to discern subtle characteristics that are not visible from only the top angle. From the viewpoint of accuracy and processing speed, our proposed method of training object detection may increase operational efficiency of green soybeans grading sorting tasks by AI.

5.1 Limitation

In this research, there are misclassifications for some classes, particularly the deformed class. These misclassifications primarily are caused by two factors: a limited number of training images in the dataset and the presence of similar features among certain grades. For instance, when the pod meets the conditions of all A_grade characters but possess a distorted shape, they are frequently misidentified as A_grade class. This is primarily because the surface of these soybeans which have A_grade characteristics are seen in the images, causing the model trained on our custom dataset to often recognize them as A_grade. Furthermore, if soybeans are being top of each other on the conveyor in the frame, the model cannot predict well.

5.2 Future Work

As mentioned in the earlier section, the experiment in this research occurred misclassifications for some classes, especially the deformed class. Deformed class denotes green soybeans with weird shapes such as curved and being stuck with another green soybean. To enhance the accuracy of detecting those characteristics, it would be worthwhile to devise an algorithm or image processing techniques which could identify distorted shaped pods. Measuring the length ratio of centroid and both ends of green soybeans Okuda et al., [5] with computer vision would be a good place to start for this research, as it tells inclinations of pod bending. If we could identify and measure the positions of those parts of green soybeans using computer vision, we can segregate between distorted shaped pods and normal shaped pods before the trained model classifies into other classes. In this way, the occurrence of misclassification would be prevented. Moreover, the case of green soybeans being top of each other in the frame should be solved by inventing an agricultural machine which can line green soybeans up straight on a conveyor. By doing this, it will prevent multiple green soybeans from getting captured in the frame.

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