Weed and Crop Detection by Combining Crop Row Detection and K-means Clustering in Weed Infested Agricultural Fields

Kumpei Ota[1,2], Jun Younes Louhi Kasahara[1], Atsushi Yamashita[1] and Hajime Asama[1]

Abstract— **Crop and weed detection is an essential technique for the automation of spot spraying and mechanical weeding. Previous studies developed crop and weed detection methods by using crop rows. However, those methods cannot perform with high accuracy when weeds are heavily present. The reason is that the crop row detection is adversely affected by the presence of large amounts of weed. And even if crop rows can be detected accurately, the methods wrongly label the weeds within crop rows as crop. Therefore, we propose a crop and weed detection method which can be used in presence of large amounts of weeds by combining crop row detection using depth data and crop/weed classification by k-means clustering. The experiment showed the effectiveness of the method by using images taken in unweeded cabbage field.**

I. Introduction

Pesticides are widely used to control pests and weeds in agriculture. However, because of concerns about the risks of pesticides to ecosystems and water quality, a trend to reduce the amount of pesticides applied to farmland has been growing in recent years. For example, the Farm to Fork strategy formulated by the EU in 2020 set a goal of reducing the use and risk of chemical pesticides by 50% by 2030 [1]. Typical measures to reduce the use of pesticides are spot spraying and mechanical weeding. However, these methods require more labor than the conventional method of spraying pesticides over the whole field. Considering the increase in food demand due to the increase in the world population, automation of spot spraying and mechanical weeding is necessary.

Crop and weed detection is an essential technology for the automation of spot spraying and mechanical weeding. Although it is not necessary to detect both crops and weeds depending on the weeding method, it is important to detect both crops and weeds with high accuracy in order to improve the quality of work. For example, in the case of weed picking robot, weeding is possible if only weeds are detected. However, in such a case, there is a large possibility that the manipulator will contact the crop. In order to reduce the risk of damaging the crop, it is desirable to detect not only the weeds but also the crop, and to plan a motion path that does not contact the crop.

In order to detect crops and weeds, Wendel et al. [2], Louargant et al. [3] and Bah et al. [4] used the regularity of crop arrangement: crops are linearly aligned, while weeds exist in irregular patterns. Concretely, these studies applied the Hough transform to a plant-extracted binary image (plant binary image) to detect crop rows. Then, they automatically labeled pixels or blobs on the crop rows as crops and pixels or blobs apart from the crop rows as weeds, and trained a supervised learning model to classify crops and weeds.

These methods, which utilize the regularity of crop arrangement, can be used regardless of type or growth stage of the crops and weeds. However, they are not effective when the number of weeds is large. There are two reasons for this. First, when there are many weeds, the Hough transform applied to the plant binary image cannot detect crop rows accurately. Second, even if crop rows are detected with high accuracy, weeds that exist between crops in crop rows would be labeled as crop, which would degrade the quality of the training data.

Therefore, the present study aimed to develop a crop and weed detection method that can be used in presence of large amounts of weed. In order to achieve the goal, a method combining crop row detection and k-means method was proposed in this study.

II. Method

A. Problem Setting

In this study, we addressed the binary classification problem of plant blobs into crop/weed in RGB-D images. We assumed a weeding robot which runs along the crop rows. Therefore, images taken in some of the crop rows were used as training data, while images taken in other rows were used as test data.

B. Concept and Overview of Proposed Method

In this study, we propose a method combining crop row detection and k-means method to perform crop and weed detection which works in presence of large amounts of weed. The cluster number k is set to two corresponding to crop and weed. If the k-means method alone is applied without combining it with crop row detection, the number of crop blobs will be significantly smaller than the number of weed blobs in weed infested agricultural fields. In that case, it becomes difficult to separate crop blobs and weed blobs with high accuracy using the k-means method. This is because clustering is performed by repeatedly updating the centroid position of

[1] Kumpei Ota, Jun Younes Louhi Kasahara, Atsushi Yamashita and Hajime Asama are with the Department of Precision Engineering, The University of Tokyo, 113-8656 Tokyo, Japan.
otakumpei@robot.t.u-tokyo.ac.jp

[2] Kumpei Ota is with Institute of Agricultural Machinery, National Agriculture and Food Research Organization, 331-8537 Saitama, Japan.

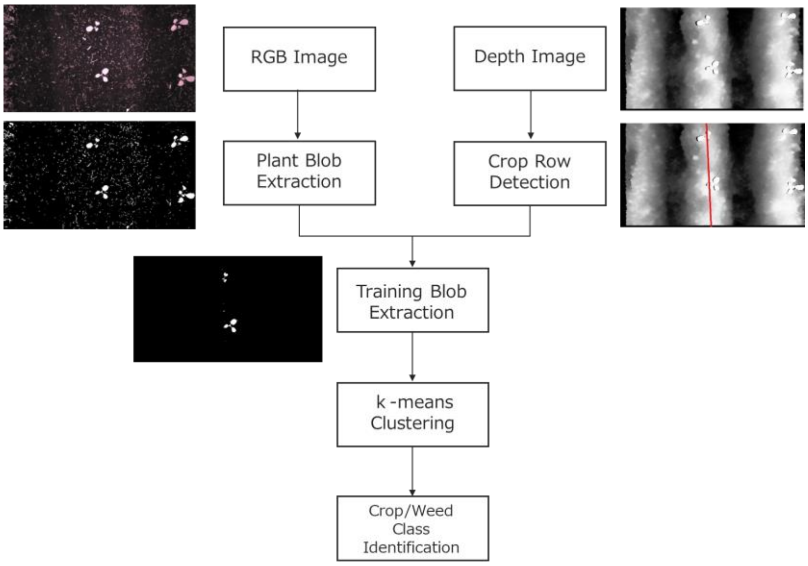


Fig. 1. Overview of training phase.

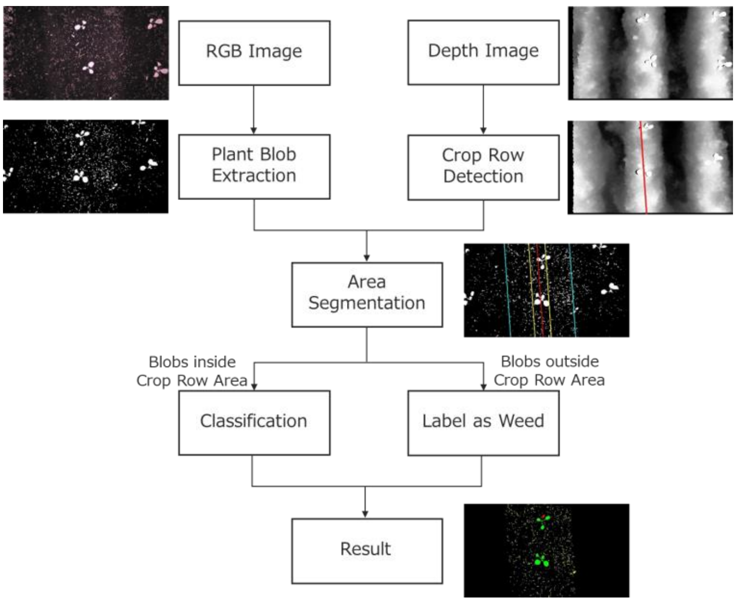


Fig. 2. Overview of detection phase.

each class and assigning the class represented by the nearest centroid to each sample in the k-means method. When the number of crop blobs is significantly smaller than the number of weed blobs, the influence of crop blobs on the centroid position update becomes relatively small. Therefore, we use the crop row detection to increase the proportion of crop blobs in the training data to improve the separation accuracy between crop blobs and weed blobs by the k-means method.

This method consists of two phases: a training phase and a detection phase. The outline of the training phase is shown in Fig. 1, and the outline of the detection phase is shown in Fig. 2. In the training phase, only the plant blobs on the crop-row line are used as training data, and the centroids of the crop and weed classes are obtained by the k-means method. In the detection phase, the fact that crops exist only within the crop row was used. The plant blobs within the crop row were classified using the centroid obtained in the training phase. All plant blobs outside the crop row are classified as weeds.

C. Training Phase

Plant Blob Extraction

The plant binary image is created by applying Otsu's method [5] to the R channel of the RGB image. Furthermore, Canny's edge detection [6] is applied to the R channel of the RGB image and the detected edges are superimposed on the plant binary image to separate the overlapping plants into separate blobs in the image. In addition, the blobs with an area smaller than 4 pixels are removed as noise.

Crop Row Detection

In this method, crop row detection is performed using depth data in order to reduce the influence of weed quantity. The flow of crop row detection is shown in Fig. 3. The crop rows are detected by removing the plant area from the depth image and fitting the wave surface. In this method, even if there are a lot

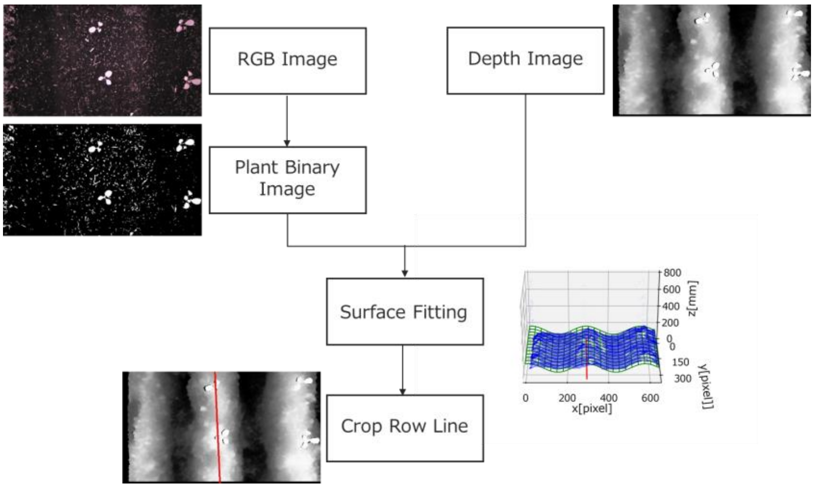


Fig. 3. Flow of crop row detection.

of weeds, crop rows can be detected by using the shape of the ground surface exposed through the gaps.

The wave surface is formed by scanning a 1D wave in the y-axis direction of the image, which is obtained by Eqs. (1) and (2).

$$z = h\cos\left(\frac{2\pi(x\text{-}x_c)}{T}\right)+b\,, \quad (1)$$

$$x_c=\frac{(\rho\text{-}y\sin\theta)}{\cos\theta}\,, \quad (2)$$

where x, y are the coordinates on the image, z is the depth, x_c is the x-coordinate of the crop line, h, T, b, ρ, θ are the parameters to be optimized by the curve fitting, which are the amplitude of the wave, the period, the height of the reference plane, the distance between the crop line and the image origin, and the slope of the crop line, respectively. Although only one set of parameters for the crop-row line is obtained from the fitting, there are multiple crop-row lines at intervals of period T in the image. We consider the crop row closest to the center of the image to be the target area of weeding. Therefore, only the line with the smallest distance from the center point of the image is adopted as the crop-row line.

Training Blob Extraction

Combining the results of plant blob extraction and crop row detection, we extract only the blobs that are connected to the crop-row line as the training data. By this process, we increase the proportion of crop blobs in the training data.

K-means Clustering and Crop/Weed Class Identification

K-means clustering is conducted to separate the plant blobs into two clusters. Features used in the clustering were the mean of R, G, B, and D for each plant blob, and blob area, perimeter length, and shape features used by Cho et al. [7]: aspect, roundness, compactness, elongation, and cube of perimeter to area by length.

After separating into two clusters, the cluster including the larger number of samples is identified as the weed class and the other as the crop class, using the fact that the number of weeds is larger than that of crops as prior knowledge.

D. Detection Phase

Plant blob extraction and crop row detection are the same as in the training phase.

Area Segmentation

A region of width T with the centerline of the detected crop-row line is defined as the target region, and only the plant blobs in the target region are used for crop and weed detection. This is because we consider only the crop row closest to the center of the image and its surrounding area to be the target of weeding work.

We define the crop-row region as a region of width $T/4$ centered on the crop-row line, and apply the following classification to the blobs within the region. On the other hand, all blobs that are not included in the crop-row region are classified as weeds.

Classification

Binary classification is performed using the centroids of the crop class and weed class obtained in the training phase. The Euclidean distance between each centroid and each blob in feature space is calculated. The blobs are classified into the class with the smallest distance.

III. Experiment

A. Test Field

The images were taken on July 16, 2021, at the cabbage field in the Gunma Prefecture, Japan. The appearance of the cabbage field on the day is shown in Fig. 4. Cabbage was sown on June 7 and transplanted into the field on July 7. No weeding was done, and many weeds were present in the field.

B. Data Acquisition System

The equipment used for image acquisition is shown in Fig. 5. An RGB-D camera (Intel RealSense D415) was mounted downward on the harvesting cart. The cart was pushed by hand along the crop rows. Images were acquired with a height of 360 pixels and a width of 640 pixels.

Fig. 4. Appearance of cabbage field

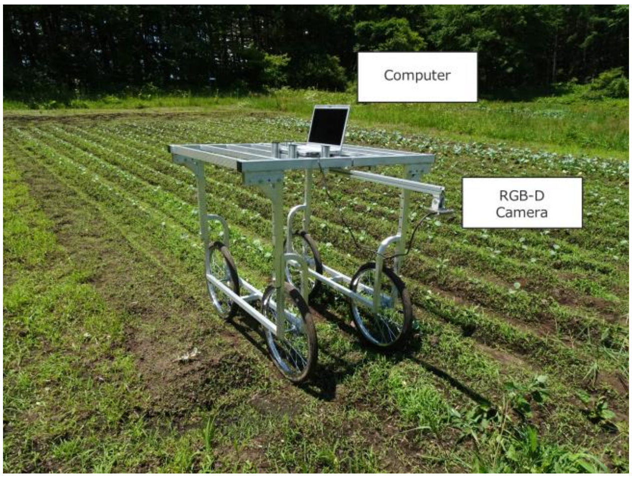


Fig. 5. Data acquisition system

TABLE I. THE NUMBERS OF CROP BLOBS AND WEED BLOBS IN TRAINING IMAGES

	Proposed	Using All Blobs
Crop Blob	42	80
Weed Blob	284	14880

C. Evaluation of Crop Row Detection

We used the image taken in one row to verify the effectiveness of the crop row detection. The absolute value of the difference between the detection results by the proposed method and the true values of ρ and θ determined by a human viewing the depth image was examined. In order to investigate the effect of the amount of weeds on the crop row detection, artificial weeds were drawn on the plant binary image and masked on the depth image. The artificial weeds were drawn as circles with a radius of 3 pixels so that the area of the plant region accounted for 90% of the entire image.

D. Evaluation of Crop and Weed Detection

To examine the effectiveness of our method, we compared it with two other methods. The first one uses k-means method, the same as our proposed method, but it uses all the blobs in the target area as training data. This method was adopted to show the importance of training data selection by combining the crop row detection and k-means method in training phase. The number of crop blobs and weed blobs included in the training data for both methods is shown in Table I. The proportion of crop blobs was 12.9% in proposed method, while the one was 0.5% in case of all blobs in the target area were used. Therefore, the difference shows that the proposed method can increase the proportion of crop blobs in training data.

The second one for comparison is based on the same concept as related works [2-4]: the plants on the crop row lines are labeled as crop and the others are labeled as weed in training phase. Therefore, the weeds on crop row lines are labeled as crops and it will degrade the performance of the classifier. This method is adopted to show that the proposed method is less affected by weeds on crop row lines. In this method, Support Vector Machine (SVM) is used as classifier instead of k-means method. An example of training data is shown in Fig. 6. Note that there are some differences in detail between this method and related works [2-4], e.g. the types of camera, the types of features, etc. although the basic concept is the same.

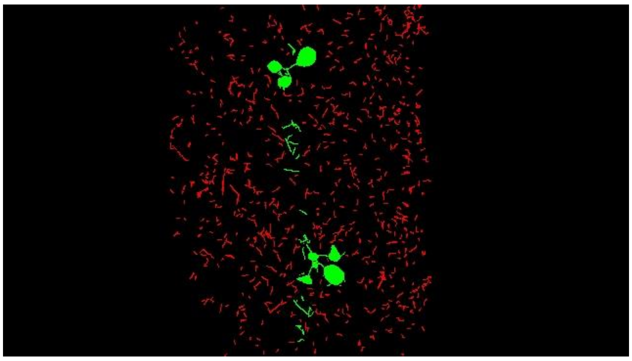


Fig. 6. The example of training data for SVM. Green blobs are labeled as crop. Red blobs are labeled as weed.

Precision and recall were adopted to evaluate the results.

$$precision = \frac{TP}{TP+FP}, \quad (3)$$

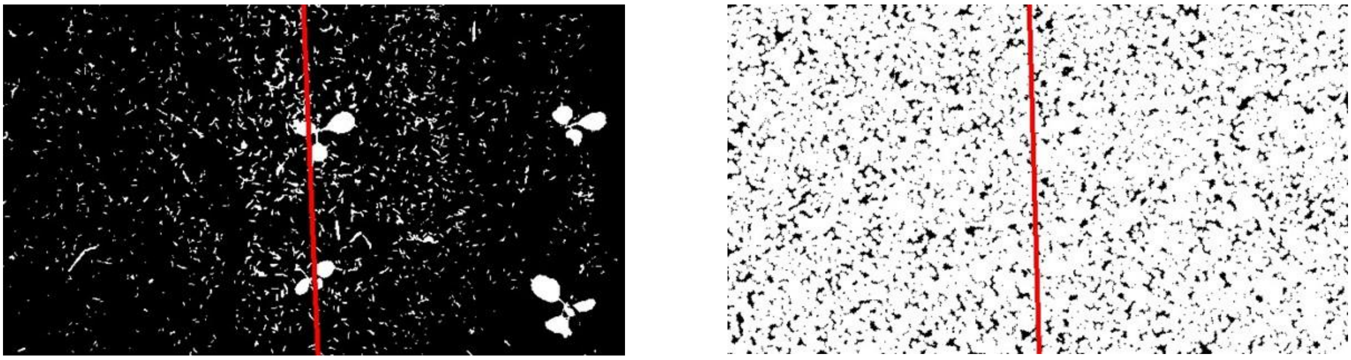
$$recall = \frac{TP}{TP+FN}. \quad (4)$$

In Eqs. (3) and (4), *TP*, *TN*, *FP*, and *FN* represent the number of true positives, true negatives, false positives, and false negatives, respectively.

In crop detection, recall is more important than precision for economic reasons. If some crops are mis classified as weeds, they are removed. It directly leads to economic loss. Therefore, F2 score was used to evaluate the total performance of crop detection. And for the same reason, precision is more important than recall in weed detection. Therefore F0.5 score was used for weed detection.

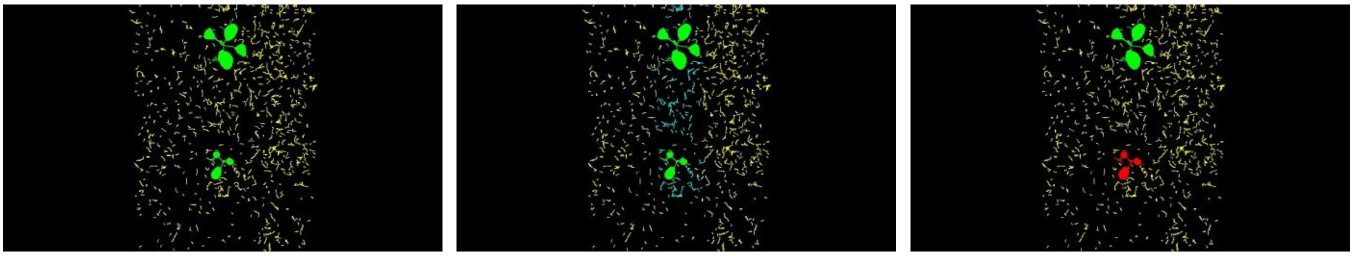
$$F2 = \frac{5 \cdot precision \cdot recall}{4 \cdot precision + recall}, \quad (5)$$

$$F0.5 = \frac{1.25 \cdot precision \cdot recall}{0.25 \cdot precision + recall}. \quad (6)$$



(a) No artificial weeds (b) With artificial weeds

Fig. 7. The results of crop row detection



(a) Proposed method (b) K-means with all blobs (c) SVM

Fig. 8 The results of crop and weed detection. Green, yellow, cyan, and red represent true crop, true weed, false crop, and false weed, respectively.

Here, the images taken in one row were used as training data, and the images taken in the other two rows were used as test data. The number of RGB-D images in training data was 30 and the one in test data was 44.

IV. RESULTS AND DISCUSSION

A. Evaluation of Crop Row Detection

Figure 7 shows the results of the crop row detection in the absence and presence of artificial weeds. The absolute values of ρ and θ obtained by fitting the wave surface are 7.5 pixels and 0.02 rad, respectively, in the absence of artificial weeds, and 8.0 pixels and 0.03 rad, respectively, in the presence of artificial weeds.

These results indicate that the proposed method can detect crop rows with high accuracy and can be used even in the presence of many weeds.

B. Evaluation of Crop and Weed Detection

The results of precision, recall, F scores of crop and weed detection are shown in Tables II and III. And examples of detection results are shown in Fig. 8. In k-means methods with all blobs, the precision and F2 value were extremely smaller compared with proposed method. As shown in Fig. 8(b), many weeds in crop rows were misclassified as crops. The performance does not reach the practical level. The results show that combining crop row detection and k-means method in training data selection is effective to improve the performance of classification.

Although the precision of SVM in crop detection is higher compared with proposed method, the recall and F2 score of SVM were small. As mentioned above, recall is more important than precision in crop detection for economic reasons. Therefore, the proposed method is seemed to be more suitable for practical use. The results show that the proposed method is less affected by weeds on crop row lines than previous methods which consider all plants on the line as crops.

TABLE II. THE RESULTS OF CROP DETECTION

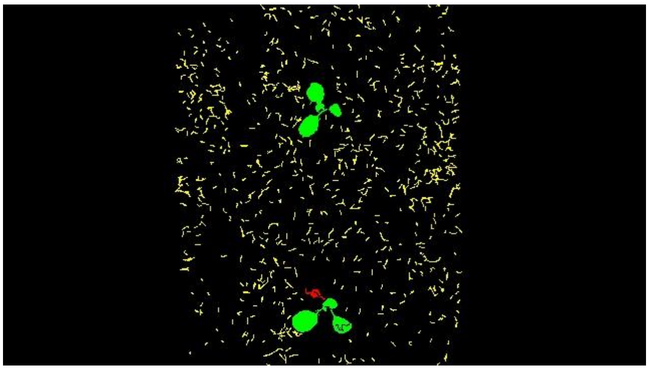
	Proposed	K-means with all blobs	SVM
Precision	0.723	0.052	1.000
Recall	0.986	1.000	0.469
F2 score	0.919	0.215	0.524

TABLE III. THE RESULTS OF WEED DETECTION

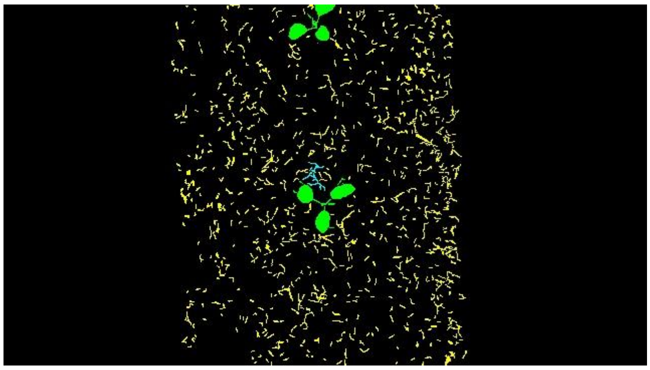
	Proposed	K-means with all blobs	SVM
Precision	1.000	1.000	0.996
Recall	0.997	0.878	1.000
F0.5 score	0.999	0.900	0.997

Figure 9 shows the examples of misclassification. In Fig. 9(a), a cabbage leaf was misclassified as weed. The cause of the misclassification seemed to be the area and shape of the leaf. The area of the leaf is small and the shape is elongated. These are similar to weeds. Therefore, the disadvantage of this method is that misclassification tends to occur when the geometric features are similar.

In Fig. 9(b), a weed blob was misclassified as crop. The cause of this misclassification also seemed to be shape similarity. The area is relatively large, and the aspect and elongation of the weed seemed to be similar to cabbage leaf.



(a) Cabbage leaf was misclassified as weed.



(b) Weed was misclassified as crop.

Fig. 9 The examples of misclassification. Green, yellow, cyan, and red represent true crop, true weed, false crop, and false weed, respectively.

This is important problem because large weeds can cause more serious effects than small one.

V. CONCLUSION

In this study, we proposed a crop and weed detection method that can be used in presence of large amounts of weed. The proposed method combined crop row detection using depth data and the k-means method. The method increased the proportion of crop blobs in the training data and improved the classification performance.

In future work, we would like to improve the classification method so that it can accurately classify plants with similar geometric features.

REFERENCES

[1] An Official Website of the European Union, “Farm to Fork targets – Progress[web page],” https://ec.europa.eu/food/plants/pesticides/sustainable-use-pesticides/farm-fork-targets-progress_en, accessed: 2021-09-06.

[2] A. Wendel and J. Underwood, “Self-supervised Weed Detection in Vegetable Crops Using Ground Based Hyperspectral Imaging,” Proceedings of the 2016 IEEE International Conference on Robotics and Automation, pp. 5128-5135, 2016.

[3] M. Louargant, G. Jones, R. Faroux, J. Noël, T. Maillot, C. Gée and S. Villette, “Unsupervised Classification Algorithm for Early Weed Detection in Row-crops by Combining Spatial and Spectral Information,” Remote Sensing, vol. 10, no. 5, pp. 1-18, 2018.

[4] M. D. Bah, A. Hafiane. and R. Canals, “Deep Learning with Unsupervised Data Labeling for Weed Detection in Line Crops in UAV Images,” Remote Sensing, vol. 10, no. 11, pp. 1-22, 2018.

[5] N. Otsu, “Threshold Selection Method From Gray-Level Histograms,” IEEE Transactions on Systems, Man, and Cybernetics, vol. 9, no. 1, pp. 62-66, 1979.

[6] J. Canny, “A Computational Approach to Edge Detection,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 8, no. 6, pp. 679-698, 1986.

[7] S. I. Cho, D. S. Lee and J. Y. Jeong, “Weed-plant Discrimination by Machine Vision and Artificial Neural Network,” Biosystems Engineering, vol. 83, no. 3, pp. 275-280, 2002.