Detecting Overgrown Plant Species Occluding Other Species in Complex Vegetation in Agricultural Fields Based on Temporal Changes in RGB Images and Deep Learning

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Abstract: Synecoculture cultivates useful plants while expanding biodiversity in farmland, but the complexity of its management requires the establishment of new automated systems for management. In particular, pruning overgrown dominant species that lead to reduced diversity is an important task. This paper proposes a method for detecting overgrown plant species occluding other species from the camera fixed in a Synecoculture farm. The camera acquires time series images once a week soon after seeding. Then, a deep learning based semantic segmentation is applied to each of the weekly images. The plant species map, which consist of multiple layers corresponding to the segmented species, is created by storing the number of the existence of that plant species over weeks at each pixel in that layer. Finally, we combine the semantic segmentation results with the earlier plant species map so that occluding overgrown species and occluded species are detected. As a result of conducting experiments using six sets of time series images acquired over six weeks, (1) UNet-Resnet101 is most accurate for semantic segmentation, (2) Using both segmentation and plant species map achieves significantly higher segmentation accuracies than without plant species map, (3) Overgrown, occluding species and occluded species are successfully detected.

1 INTRODUCTION

In the field of agriculture, with modernization, a cropping method characterized by the cultivation of specific plants as monocultures and the use of chemical fertilizers and pesticides has been adopted to enhance food productivity (Tudi et al., 2021). However, such conventional farming practices render plants vulnerable to pests, diseases, and weeds. Furthermore, the continuous and increasing use of chemicals not only disrupts the soil ecosystem but also reduces the biodiversity of agricultural land and its surrounding environment (Conway and Barbie, 1988; Geiger et al., 2010; Savci, 2012). Particularly, reducing biodiversity is severe in conventional farming, prompting the need for achieving more sustainable farming methods (Norris, 2008).

In response to these issues, a new method called “Synecoculture” has been proposed. Synecoculture is an agricultural method in which various plant species are grown in mixed, densely planted environments in a single farm to promote self-organization of the ecosystem, thereby increasing the biodiversity of the farm and producing useful crops by enhancing ecosystem functions. On farms where Synecoculture is practiced, the rich biodiversity results in intensive competition for survival among plant species. It is believed that plants' inherent self-organization ability allows the plants to grow without using pesticides or chemical fertilizers. Therefore, Synecoculture is considered to be a more sustainable agricultural practice than conventional agriculture because Synecoculture can increase the productive capacity of multiple crops as the diversity of plant populations expands.

Synecoculture is also expected to convert deserts and wild areas into green spaces in the future. In such cases, Synecoculture plantations could have very large areas, and automation of their management is essential. However, the vegetation in Synecoculture plantations is so complex as mentioned earlier that it is difficult to automate the management using conventional agricultural machineries.

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The third and fourth coauthors of this paper focus on the development of an automation robot designed for the management of Synecoculture (Tanaka et al., 2022). The 1st, 2nd and 5th coauthors are specifically investigating the visual capabilities of this robot. Our objective is to automate crucial tasks such as pruning overgrown dominant plants, seeding, and harvesting crops. Especially in Synecoculture farms, it is important to increase plant diversity and the soil should not be exposed. Therefore, it is not always right to prune all the dominant species that are commonly referred to as weeds. On the other hand, if these dominant species are not pruned at all, only these species will thrive, and they will overgrow and inhibit the growth of other plants.

In order to prune dominant species that are overgrown, occluding other species, and reduce diversity, we have been working on a method using image processing technologies that segment dominant plants in the image acquired by the camera observing Synecoculture farms and estimate pruning points in a densely overgrown plantation. However, due to its occlusive environments, it is difficult to accurately segment dominant species and estimate pruning points in agricultural areas with densely mixed vegetation (Ide et al., 2022). It tunred out to us that it is difficult to identify vegetation from an image after plants have thrived.

The method proposed by this paper utlizes the fact that there is little occlusion between plants during short duration after seeding and the segmentation accuracy for each plant is high. Our proposed method acquires time series images using a fixed camera according to some constant interval starting from a time instance soon after the seeding. Each image of the time series images are segmented, and plant species map count the number of appearance of each plant species at each pixel in the segmented images over the time. By using the plant species map and segmented time series images, even if useful species are covered with other overgrown species, information such as occluding areas, which should be pruned, can be obtained.

This paper demonstrates that the utilization of time-series data enables a more accurate segmentation of the vegetation in Synecoculture environments. Consequently, we have developed the capability to identify plants that cause occlusion, which is helpful to maintain the Synecoculture farm automatically.

2 RELATED WORKS

Among agricultural robots already in practical use, Raja et al. detected and pruned weeds that inhibited the growth of useful species without pruning them (Raja et al., 2020). They marked tomato and lettuce stems, removing 83% of weeds without pruning. However, due to the intricate and densely mixed vegetation in this study, controlling specific plant species through marking is deemed impossible.

In the field of machine learning, many studies have been conducted to estimate plant species. In recent years, deep learning has made it possible to recognize a wide variety of plant species. Mortensen et al. reported that the semantic segmentation model achieved 79% accuracy, showing the effectiveness of data augmentation and fine-tuning in plant species estimation (Mortensen et al., 2016). Picon et al. used Dual-PSPNet to classify diverse plant species, achieving higher accuracy than the original PSPNet model (Picon et al., 2022).

However, in all studies, recognition accuracy was lowered for plants under the presence of occlusion, which indicates that the presence of occlusion is a major issue in classifying plant species using images. To tackle the occlusion problem, Yu et al. improved recognition accuracy over existing learning models by developing original learning models suitable for the presence of occlusion (Yu et al., 2022). However, in Synecoculture farms, the sizes of plants vary due to individual plant growth, which results in more complex occlusions.

Therefore, it is necessary to enable highly accurate plant species recognition in Synecoculture environments, which could yield severe occlusions. More specifically, when pruning, it is important to be able to identify not only the plant species that are visible from the camera, but also the plants that are covered underneath.

3 PROPOSED METHOD

In Synecoculture farms, despite occlusions, it is crucial to grasp the vegetation and identify occluded useful species and occluding dominant species.

Our method leverages the initial stages of Synecoculture farms, where occlusion is infrequent right after seeding and germination. In these early phases, small and isolated individual plants allow accurate segmentation with existing models. As shown in Figure 1, Our proposed method consists of acquiring time series images, semantic segmentation, generating the plant species map and detecting overgrown plant species occluding other species.

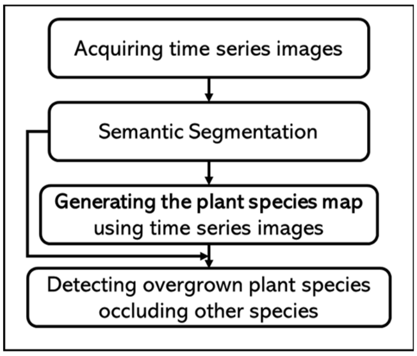

Figure 1: Over-view of our proposed method.

3.1 Semantic Segmentation

3.1.1 Model Architecture

UNet and Deeplab V3+ have been used as the main learning models in many studies using semantic sesgmentation with deep learning on plants (Li et al., 2022; Wang et al., 2021; Zou et al., 2021; Kolhar and Jagtap, 2023). In these studies, UNet and Deeplab V3+ tend to perform better than other basic learning models such as PSPNet and SegNet. Therefore, as a result of comparing UNet and Deeplab V3+ in Section 4.1.2, this paper uses Resnet101-UNet for the subsequent processes such as for creating plant species map.

Resnet50 and Resnet101 are used as the backbone of the encoder part of the system. Recently, other studies have shown that they are effective as the backbone of semantic segmentation models (Bendiabdallah et al., 2021; Nasiri et al., 2022; Sharifzadeh et al., 2020).

Many studies have shown that fine-tuning of a pre-trained model with a large dataset using a small number of their own images is effective; therefore, we use a backbone that was previously trained by ImageNet and trained it in the form of fine-tuning.

In this paper, Section 4.1 investigate learning models suitable for plant species detection in a Synecoculture environment by changing the combination of these encoders and decoders.

3.1.2 Implementation of Semantic Segmentation

In this process, we obtain the semantic segmentation result from each time series image. Before predicting the species at each pixel, the original 1280 x 720 pixels image was cropped into 475 square pixels before training models and prediction to reduce the burden of computers. To prevent a decrease in accuracy at the edges of cropped images, we used the following method for image cropping. First, we applied 400 pixels of zero padding to the outside of a 1280 x 720 pixels image and cropped the image to 475 x 475 pixels from the edge. When cropping the image to 475 square pixels from the edge, we set the strides to 100 pixels to generate overlaps between the crop images. Each crop image outputs a semantic segmentation result with a pre-trained model. Since the overlapping regions of multi crop images produce multiple predictions for a single pixel, the most frequently predicted class was used as the prediction class for that pixel. By outputting semantic segmentation results as described above, a more accurate 1280 x 720 pixels prediction result can be obtained.

3.2 Creating Plant Species Map

To improve the accuracy of plant species estimation under severe occlusions, the plant species map for each species is generated using the plant species estimation results from time series images. Figure 2 overviews how to create the plant species map.

First, the field is divided into several (six in this paper) areas. A fixed bird's eye view camera observes each area as explained in Section 4.2 and acquires RGB images at some predefined constant interval.

Next, for each of the acquired time series images, we estimate the plant species at each pixel using a semantic segmentation model that has already been trained using training images as explained in Section 3.1.2. The output pixels by pixel-wise plant species semantic segmentation results are then layered for each plant species, as shown in Figure 2, where each pixel of each plant species map stores a value indicating whether or not that plant species is present: specifically, 1 if the corresponding plant species is present, and 0 otherwise.

Finally, the value of each corresponding pixel in all the plant species layers are added over all of the time series images so that the final plant species map is obtained. This allows the presence of a plant to be inferred from the plant map even under difficult-to-recognize situations such as severe occlusions. That is, even if a particular plant species is covered by other plant species from some time instance, the occluded plant species map is recorded as non-zero pixels values, which means that the plant species map is robust against occlusions.

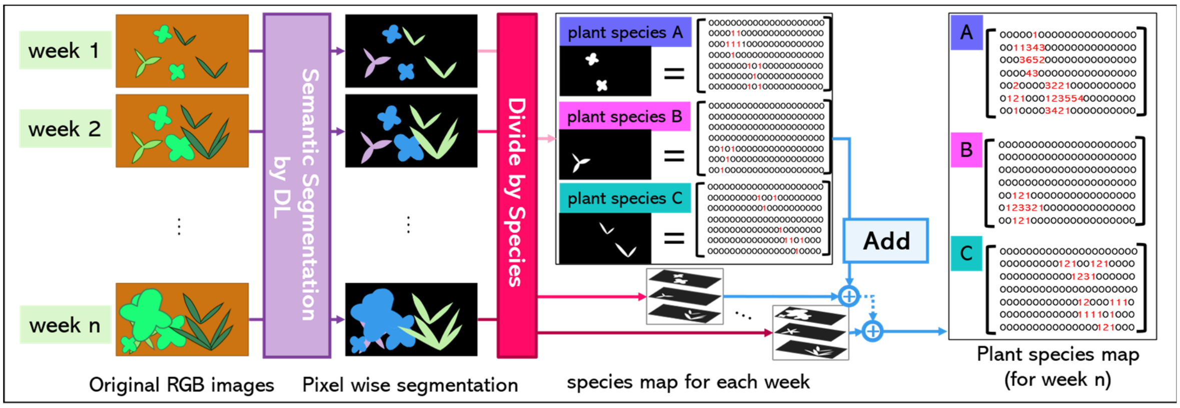

Figure 2: The method of creating plant species map.

3.3 Occlusion Area Detection

Even if a plant species is not detected in the segmentation result of the image acquired at some time instance, if that species is detected in the segmentation result of an earlier image, we can know the existence of that species from the plant species map. Therefore, if a plant is not detected in the segmentation result of the image at some time instance and is confirmed that plant's existence in the plant species map, then that species can be judged to be occluded by other species from an earlier time instance.

The specific procedure for judging whether some plant species overgrows from a time instance, occluding other species, is as follows.

As a general case, we explain the case in which the n-th week's overgrowth is to be detected, where $2 \leq n \leq 6$. First, in the $(n - 1)$-th week's plant species map, whether the useful species (in this paper, green pepper) exists at each pixel is checked. Next, in the n-th week's segmentation result, whether the useful species exists is checked at the pixels whose image coordinates are same as those of the $(n - 1)$-th week's plant species map's pixels at which the useful species exists. Finally, if all of the following three conditions (1) to (3) are satisfied at a pixel, our proposed method judges that a dominant species (apple mint or green foxtail) overgrows at the pixel at the n-th week, occluding the useful species.

(1) At a pixel in the $(n - 1)$-th week's plant species map, the useful species exists.
(2) At the n-th week's segmentation result's pixel that corresponds to the pixel described in (1), the useful species does not exit.
(3) At the n-th week's segmentation result's pixel described in (2), a dominant species exists.

The above-mentioned processes are repeated for $2 \leq n \leq 6$.

As our future work, the obtained positional information on the overgrown, occluding non-useful species could be utilized for determining the positions to be pruned by our robotic system.

4 EXPERIMENTS AND RESULTS

4.1 Semantic Segmentation Model

As explained in Section 3.1 we compared the common semantic segmentation models to chose appropriate deep learning model for our data.

4.1.1 Training of Models

The image data used for training the models were acquired once a week between May 2022 and June 2023 in farms in Akiruno, Tokyo, and Oiso, Kanagawa Prefecture, where Synecoculture is actually implemented. The data were acquired using an Intel RealSense D435 RGBD camera, which captured RGB images from a height of approximately 1.5 meters above the ground, looking vertically downward at the farms.

A total of 137 1280 x 720 pixels images were acquired, 127 were used to train the models and the remaining 10 were used to test the models. The acquired images were annotated so that "green foxtail," "apple mint," "green pepper," "other plants," and "unvegetated area" were correctly labelled as pixel wise segmentation. The train images were cropped to 475 x 475 pixels before training.

Train images were further divided into train and validation at a ratio of 7:3 for the training. In addition, to compensate for the lack of datasets, data augmentation was applied to train images only. First, we applied the gamma correction, which is considered effective for plant detection (Saikawa et al., 2019). In addition, we applied the Random Shadow, Random Sun Flare, and Random Contrast functions. Random Scale, Random Rotation, Color Jitter, and Random Horizontal Flip, which are commonly used, were also applied.

The GPU used for training was a 24GB NVIDIA GeForce RTX 3090 with a learning rate of 0.001, Adam as the optimization function, and a batch size of 16. During the training process, mean IoU which is explained in Section 4.1.2 is calculated, and the one with the highest mean IoU value of validation during each 200 epochs was used.

4.1.2 Model Performance Assessment

10 images of Synecoculture farms were used to test the models, as described in section 4.1.1. To obtain semantic segmentation results for each model, the process described in section 3.1.2 was performed.

After the segmentation results for Deeplab V3+ or UNet combined with Resnet50 or Resnet101 as backbone were obtained, their accuracy was calculated. Table 1 compares the accuracy of the segmentation models on test images.

According to Table 1, overall UNet performs better than DeeplabV3+. In particular, all the indices of UNet with Resnet101 as the backbone are the highest, while UNet with Renet50 almost the second highest.

Table 1: Comparison of segmentation models.

Model	Recall %	Precision %	F1 %	mIoU %
Resnet50-UNet	72.55	78.32	74.82	61.01
Resnet101-UNet	**77.63**	**79.19**	**78.02**	**64.58**
Resnet50-DeeplabV3+	73.38	76.24	74.48	60.40
Resnet50-DeeplabV3+	73.49	76.09	74.18	59.93

4.2 Acquisition of Time Series Data

As explained in Section 3.2, time series images for the plant species map were acquired.

For acquiring time series images, 1280 x 720 pixels RGB images were acquired once a week over the six weeks from May 2023 using an Intel RealSense D435 RGBD camera pointing vertically downward from a bird's eye view fixture installed at the top of the 110mm-high frame. The camera was installed in the same position as that of the agricultural robot under development. The farm is divided into six areas, at each of which the camera was placed, so that (= 6 times 6) time series images of the Synecoculture environment were acquired for the six areas over a total of six weeks. In addition, we pruned the overgrown apple mint and green foxtail in 7-th week and acquired post-pruning images in the same way as the method explained earlier. We also applied black masks to equipment in the images that had no relevance to the plants.

4.3 Segmentation Results in Time Series Images

We then segmented the six images for each week using the Resnet101-UNet trained model, applying the method described in Section 3.1.2. Figure 3 shows examples of the segmentation results obtained by the Resnet101-UNet trained model in the four weeks out of the six weeks. As shown in Figure 3, the green pepper, which was completely visible in early weeks, is covered by apple mint and green foxtail, which tend to dominate after week 5, and only a part of the leaves of the green pepper is visible due to the occlusion caused by the overgrown apple mint and green foxtail. To solve this problem, as described in Section 3.2, the plant species map is proposed by this paper.

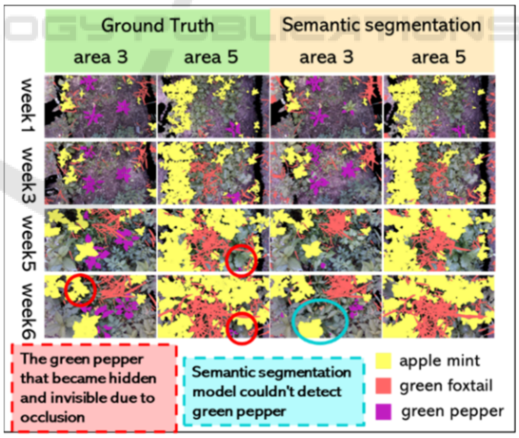

Figure 3: Segmentation results for each week.

4.4 Creating Plant Species Map

Figure 4 compares segmentation results for each single image with the plant species map for all over the six weeks, where the color in the right three columns indicates as follows: dark blue and bright orange if the count at a pixel is small and large,

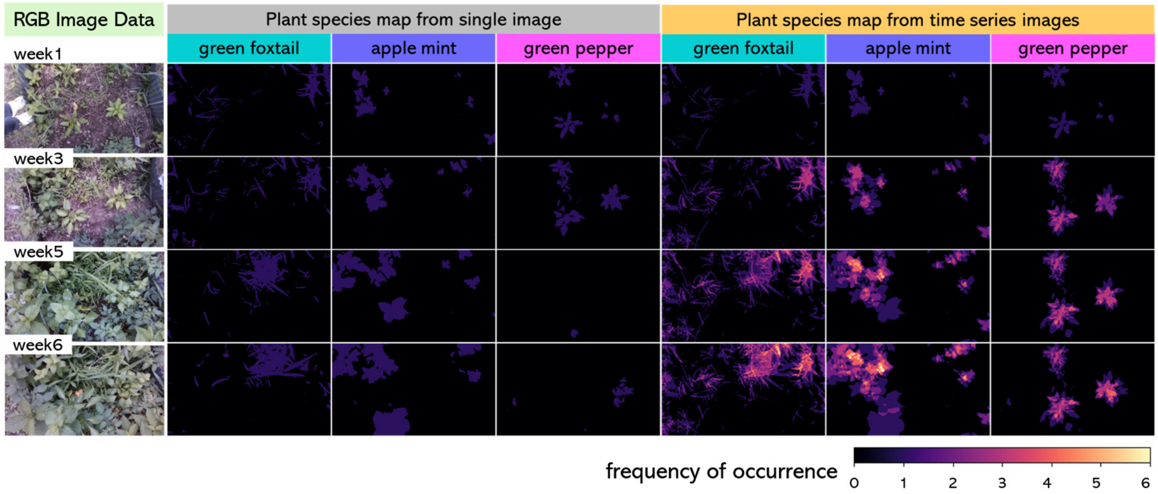

Figure 4: Visualization of plant species map.

Table 2: Comparison of segmentation accuracies with/without plant species map.

"with" / "without"	Class (plant species)	Precision %	Recall %	F1 %	mean F1 %
"without" (Only using week 6's segmentation result, without using plant species map)	Green foxtail	**83.49**	46.18	59.47	46.68
	Apple mint	**97.51**	56.17	71.28	
	Green pepper	**88.43**	4.90	9.28	
"with" (plant species map from our proposed method)	Green foxtail	72.24	**88.71**	**79.63**	**80.32**
	Apple mint	95.05	**93.25**	**94.14**	
	Green pepper	83.09	**56.41**	**67.20**	

respectively, while 0 or 1 in case of the segmentation for single images in the middle three columns. As shown in Figure 4, when a same plant species keeps present and visible at the same place over weeks, the value of the corresponding pixels in that plant species map is increased, displaying brighter. In addition, we can confirm that even after a plant species is occluded by other species, we can locate the occluded species in the map.

Next, we tested the validity of the plant species map. Ground truth plant species map which indicates the existence of each plant species for each pixel are created from annotation data (ground truth of semantic segmentation) for each time series image. Table 2 shows the segmentation accuracies of the 6-th week's plant species map ("with") and semantic segmentation results which is predicted from only one image of 6-th week without the plant species map ("without"). According to Table 2, the plant species map provides more accurate segmentations than segmentation without using plant species map. In particular, the *Recall* for all three classes (plant species) are significantly lower in the case of the "without" results, which using the 6-th week's image only, without using plant species map, indicating that many plants are missed. The plant species map, being additive, yields a lower Precision due to false positives. However, the higher F1 score, representing overall accuracy, suggests its effectiveness in identifying complex vegetation.

4.5 Overgrown Plants Detection

Figure 5 shows examples of the result of using the plant species map to detect areas occluded by dominant species. In Figure 5, apple mint and green foxtail occlude green pepper. From a single-week segmentation result, locating occluded plant species under overgrown conditions is challenging. However, by performing the algorithm, explained in Section 3.3, for the plant species map and segmentation result, even plants that are completely occluded can be detected.

Thus, we have confirmed that the plant species map provides useful information for pruning. Our future step is to develop a specific pruning algorithm using the information obtained from the plant species map.

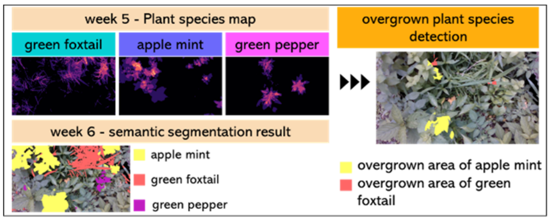

Figure 5: Results of overgrown plants detection.

5 DISSCUSION

To confirm the effectiveness of the proposed method for detecting overgrown, occluding plant species (Section 3.3), in 7-th week, we manually pruned the dominant plants occluding the useful species (green pepper) so that the useful species is visible. Figure 6 compares the location of the green peppers obtained by Section 3.3's method, which uses the plant species map in the 6-th week, with the green peppers in the segmentation result of the RGB image after pruning apple mint and green foxtail in 7-th week as mentioned earlier. Figure 6 shows that the position of the green pepper obtained by the plant species map is almost same as the actual position of the green pepper. In particular, the locations of the roots of the green pepper have not changed since the time of sprouting; so, it can be said that maintaining the past positional information by time series information is effective for understanding vegetation in an environment with severe occlusion.

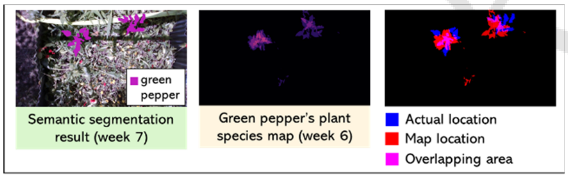

Figure 6: Checking the position of the green peppers.

6 CONCLUSION AND FUTURE WORK

This paper has proposed a method for detecting overgrown plant species occluding other species from bird's eye view camera images acquired in Synecoclture farms. Conventional methods for identifying vegetation from a single image using semantic segmentation based on deep learning has difficulty in identifying complex vegetations in Synecoculture environments. To tackle this issue, our proposed method consists of acquiring time series RGB images, performing semantic segmentation for each of the time series images, creating plant species map, and detecting overgrown species occluding other species.

The bird's eye view camera acquires time series images at a constant interval (in this paper, once a week) soon after seeding. We then apply semantic segmentation to each of the weekly images using a deep learning model so that areas of the plant species (in this paper, "apple mint", "green foxtail" and "green pepper") are segmented. The plant species map consists of multiple layers corresponding to the segmented species, and at each pixel in each layer, the number of the existence of that plant species over the weeks is stored. Finally, we combine the semantic segmentation results with the (one week) earlier plant species map so that occluding overgrown species and occluded species are detected.

Results of experiments using the 36 (= 6 images (acquired at 6 places) times 6 weeks) time series images are summarized as follows.

- It turns out that UNet using Resnet101 as the backbone achieves higher segmentation accuracies than Resnet50 as the backbone or Deeplab V3+. UNet-Resnet101 is decided to be used for the semantic segmentation for each of time series images.
- As a result of comparing results of semantic segmentation "with" and "without" the plant species map, "with" achieves much higher accuracies than "without".
- Using the segmentation result and plant species map, areas of occluding, overgrown species and occluded species are successfully detected.

In this paper, only green pepper was targeted as a useful species and apple mint and green foxtail as dominant species. However, since more plant species are mixed and densely populated in Synecoculture environments, our future work includes developing a method that can deal with a larger number of densely mixed plant species. In addition, based on this, a method for determining the positions to be pruned by our robotic system needs to be achieved.

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