Yield Monitoring Service with Time Series Representation of Growth from Crop Images

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***Abstract*— Due to the development of ICT technology and the explosion of data, various technologies such as smart farms and smart greenhouses have been applied to the agricultural sector, helping farmers a lot. This paper aims to process and utilize crop image datasets collected periodically from a strawberry greenhouse cultivation environment to analyze and monitor crop growth and yields. In addition to the time-series data collected by measuring environmental variables such as temperature, humidity, light intensity, and carbon dioxide concentration, growth-related data are needed to monitor fruit growth and predict yield. Rail cameras were installed on the testbed to collect image data on strawberry every certain time in a specific section, and to construct a time-series image dataset by detecting objects for each stage of strawberry growth. Due to the characteristics of strawberries, we represented the crop images into growth monitoring data applied to the entire fruit of the testbed or crop clusters, not to each fruit. In addition, it can be useful for various use cases if the represented growth-related time series data and sensor data are properly used together.**

Keywords—Smart Farm, Precise farming, Data preparation, Time-series data, Object detection, Crop monitoring, Yield monitoring

I. Introduction

With the rapid development of various information and communication technologies, the latest ICT technologies such as IoT, cloud, big data, and artificial intelligence technologies are applied in the agricultural sector, giving great help to the industry [1]. Smart Farm is an intelligent farm that provides convenience by observing the growth environment of crops without time and place restrictions and managing them through remote control. It can greatly help improve quality and productivity in crop cultivation, such as acquiring various data generated in a smart farm environment from installed sensors, analyzing them to create an optimal growth environment, or detecting and preventing abnormal situations.

Many interests and various studies have been conducted that have created a smart farm environment for crop cultivation. M. Cruz proposed IoT platform integrates various monitoring services into one common platform for digital farming [2]. They used a detection model for leaf diseases and tried to solve the problem by looking at them with environmental variables. Y. Chen developed an automatic strawberry flower detection system for yield prediction with minimal labor and time costs using orthoimage dataset [3]. Kierdorf proposed dataset comprises weekly RGB and multispectral UAV orthophotos and image time-series of individual plants reflecting weekly plant growth [4].

In order to create an automatic smart farm monitoring environment, it is necessary to be able to automatically measure not only environmental variable data measured through sensors but also growth-related dataset. This paper aims to collect and utilize growth-related time-series data so that growth and yield can be analyzed and monitored using strawberry image data collected periodically in a strawberry greenhouse cultivation environment. For that purpose, rail cameras were installed on the testbed and images of crops were accumulated for time-sequencing. In this paper, we propose how to represent and utilize the accumulated strawberry image sequence data. We automatically represented the collected data as growth-related time series data, which is expected to help analyze growth processes and monitor yields.

II. Testbed and Dataset

Strawberry smart greenhouse is being managed by Eco-friendly Agricultural Research Center of Kyungpook National University and located at Gunwi, South Korea. The greenhouse is Venlo type and consists of 3 iron beds with ventilation fan,

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shading and warming screen, irrigation facilities and so on. For the data acquisition, we installed several sensors to collect the environmental variables and rail cameras to collect the growth-relevant dataset.

There are 1 temperature sensor, 1 humidity sensor, 1 CO_2 sensor, 2 soil sensors and 6 quantum sensors to collect the optimal environment variables on the testbed. To measure the growth-related data, we used rail cameras to capture the crop images. There are 4 rail cameras move back and forth to capture the whole testbed. In order to analyze the growth of the same crop, it is configured to take pictures only at specific locations in several places. Fig. 1, an example of acquired image data, was taken on the evening of February 8, 2023 at line 1, position 13. There are 30 positions for each line, and each position is a fixed position 40cm away from the standard position.

Fig. 1. Crop image data taken at a specific location (Line:1, Position: 13)

III. Growth Dataset Preparation

There are various crop growth indicators like size of crops, stages of ripening, height of plants, size of leaves and so on. In order to configure a smart farm to monitor crops, it is very important to collect the appropriate data needed for analysis. It is very difficult to acquire growth information using image data of crops. In the past, experts or farmers directly measured the size or counted the number of crops, but it is impossible to accurately obtain the corresponding values using image dataset.

As you can see in the image data, it shows not just one crop, but several crops. Therefore, we need some detection models to determine where each crop is located in one image data and what growth stage it is in. We used YOLOv8 [5] as a model for detecting strawberry fruits, and used strawberry growth cycles as labels, which were divided according to flower, receptacle, and various stages according to maturity. Strawberry fruit growth cycles go through various processes from flower buds to fruit ripening red. YOLOv8 was used as a detection model because it is lightweight and has good performance to work well in the embedded device of the edge camera.

Fig. 2 shows the results of detection models using Fig. 1 image. The results show the time of image was taken and the line of testbed and position of the camera. The object list represents the growth stage and location of all detected crops. For each continuous image data at the same location, information about the position and growth stage of the fruit can be obtained using a detection model. Using this continuous information, we can represent a consecutive dataset that shows how the position of clusters and stage of crop changes.


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    "position_idx": 13,
    "angle": 0,
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            "class": 0,
            "position": [
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                583.5,
                69.0,
                89.0
            ],
            "confidence": 0.9272745847702026
        },
```


Fig. 2. Examples of detection results from Fig. 1

IV. Yield Monitoring Applications

After establishing a continuous growth-related dataset, it can be applied to various crop monitoring scenarios. In order to monitor crops automatically, it is very difficult to track each detected object every frame. Crops can become fruits and fall down, or they can be occluded by each other, so the location can be changed a lot. Therefore, crop monitoring was applied to the crop clusters or entire testbed, not to each crop.

A. *Monitoring the crop clusters*

From an agricultural point of view, it is very important to consider the growth cycle of strawberry fruits in each fruit clusters in determining the yield of strawberries. Since fruits belonging to the same fruit cluster tend to grow similarly, tracking by fruit cluster is helpful in predicting or analyzing yields and trends. Therefore, it is necessary to define the fruit clusters before monitoring each fruit clusters.

In order to define the fruit cluster, image data taken at a fixed position is used to obtain information on fruits detected through the object detection model presented above. Using this information, the distance between the detected fruits is appropriately calculated and clustered into the same crop cluster. Fig. 3 depicts the result of clustering among the same fruit clusters in one image. A large number represents the ID of the crop clusters. It is possible to recognize a fruit cluster through a simple process by gathering nearby objects among the detected objects.

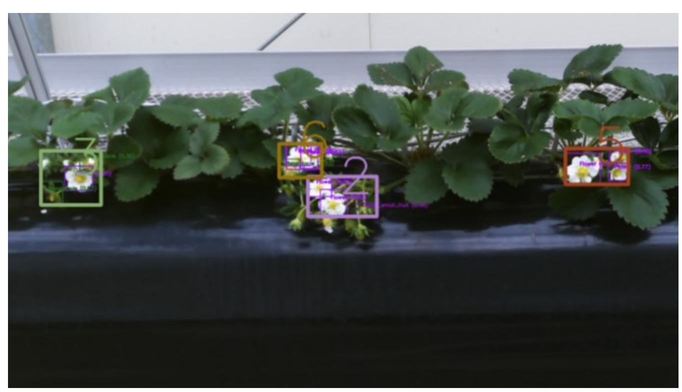

Fig. 3. Clustering result from single image

After defining a fruit cluster for each frame, it is necessary to track how the same fruit cluster moved from continuous images, and how the objects contained in that cluster change.

Data is collected twice a day, and due to the characteristics of the strawberry, the position change between each fruit cluster is not large. Therefore, each of the fruit clusters easily tracked the same clusters in each frame by utilizing a distance-based matching method and part of DeepSORT [6], a representative method of multi-object tracking.

Fig. 4 is the result of tracking the crop clusters using the continuous image sequence dataset. These 4 images were taken in the same line, same position but different time. The bounding box is the part containing the detected objects, and the number written in large next to it is the id of the corresponding fruit cluster. The results show that a particular fruit cluster actually tracks the same fruit cluster well. Therefore, it is possible to determine what stage of fruit there are in each fruit cluster at a specific time in time at a specific location. However, there are some difficulties to track the location of the same crop clusters because the detected results are different frequently.

Fig. 4. Tracking result from consecutive image

B. *Monitoring the crops from the entire testbed*

By monitoring the crops on the testbed in the entire area, you can identify the life cycle and overall trends of the crops over time for all crops, not just specific crops. We can represent and collect time-series data that has growth stage class information and the number of each class in the entire testbed at a specific time. Collected images including all the crops in the testbed are required, and the camera's fixed shooting positions should be set well to avoid overlapping areas. Through this method, the growth stage, the number, and the size of objects detected for the entire testbed can be known, and how they change over time can be tracked. You can monitor the overall growth status of cultivated crops by date.

Fig.5 depicts the analysis result of detected fruits from line 4 of the testbed. Each line has 30 shooting points and images rarely overlap. We can check the growth stage and number of all objects present at a particular time with the corresponding results. Also, we can know the growth trend of the overall fruits through the results. the growth stage and trend of the overall fruits can be known. In addition, the dataset was constructed by representing not only the number of fruits but also the area of the detected objects, which would be of great help in predicting the yield if the size of the fruit was considered.

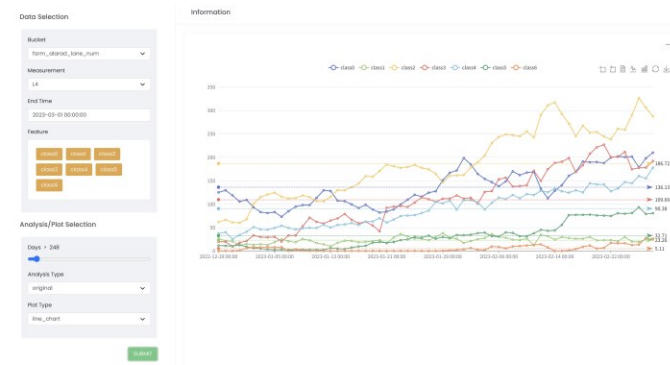

Fig. 5. The analysis results of detected fruits from the testbed line 4

C. *Combination with sensor data*

If growth-related data and values of sensor data near the corresponding location are used for monitoring together, they can be used in a more diverse way. Fig. 6 is a visualization of the sensor values collected from the greenhouse. We know the location of pre-installed sensors, and comparison and analysis with growth data of fruits close to the sensor will be of greater help in monitoring the growth environments.

By monitoring the growth data of the specific strawberry clusters, it is possible to analyze the cause of delay in growth or prediction of yield with the nearest sensor values. Also, with monitoring growth data for the entire testbed, it is possible to predict growth trends and overall yield. For example, if you know in advance that the temperature is high throughout the year, it can be faster than the existing growth rate, making it easier to prepare for cultivation early. Conversely, when the growth rate of crops is slower than in the normal period, it is also possible to find and solve the cause of various environmental variables through sensor values.

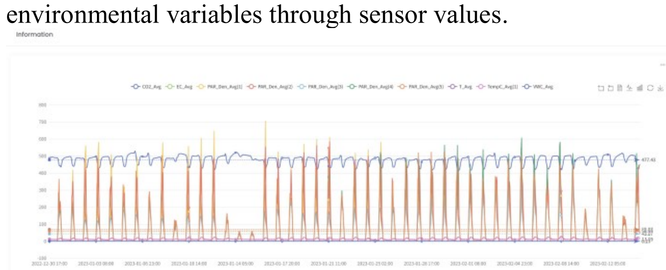

Fig. 6. Collected sensor data from the greenhouse

V. Conclusion

In this paper, we proposed how to represent and utilize the accumulated strawberry image sequence data so that it can be used for effective monitoring of crops. To detect the growth process of strawberry, a pretrained YOLOv8 model was used and crop growth status were divided into 7 stages. In addition, since it is important to monitor the growth process of each fruit clusters due to the characteristics of strawberries, new time-series data were represented using distance-based clustering and tracking the same fruit clusters of consecutive data. Also, it is possible to monitor the overall growth status of cultivated crops by date by configuring a time-series dataset by detecting fruits for the entire testbed. If the represented growth data is appropriately used with environmental sensor data, it is expected that it can be applied to various scenarios such as managing an optimal growth environment, predicting yields, or detecting abnormal situations.

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