

Growth Estimation Sensor Network System for Aquaponics using Multiple Types of Depth Cameras

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Abstract—There is an urgent need to automate and improve the efficiency of agricultural work because traditional agricultural work becomes a heavy burden for the elderly who makes up many of the agricultural workers. Therefore, in recent years, aquaponics is attracting attention as a good solution for the problem. Aquaponics is an efficient farming system that combines aquaculture and hydroponics. In the system, the bacteria decompose fish excrement, the plants absorb the decomposed excrement as nutrients, and the purified water returns to a fish tank. This cycle is automated to greatly reduce the amount of consumption of water and fertilizer. In order to keep the accurate cycle, the system should not only manage the environment so that the bacteria can properly decompose fish waste, but also measure the growth condition of the plants and fish accurately. However, the automatic estimation of the growth rate of the fish in the water is a difficult problem because the existing camera-based method cannot easily be applied to the fish living in the water. Therefore, in this study, we propose a new sensor network system with a function to quantify the size of fish as well as plants by utilizing not only a general depth camera that uses infrared rays but also a stereo camera with multiple cameras. Through the performance evaluation, it is confirmed that the proposed method can estimate the leaf area of plants and the standard length of the fish with high accuracy.

Index Terms—IoT, aquaponics, depth camera, growth rate, MaskR-CNN

I. INTRODUCTION

In recent years, the decrease in the number of people working in agriculture has become a serious problem in Japan [1]. The main reason of the problem is a huge burden of the daily farm work, hence there is a need to automate and improve the efficiency of the work. In order to realize efficient work of the agriculture and to obtain stable income, aquaponics is attracting attention as the next generation of circular agriculture. Aquaponics is sustainable agriculture that combines hydroponics and aquaculture to achieve both productivity and environmental friendliness [2]. The overview of the aquaponics system is shown in Fig. 1. This system does not require use of chemical fertilizers because bacteria decompose the fish waste and produce nutrients for the plants. In addition, it is also attracting attention as a sustainable agriculture method because the use of the amount of the water can reduce by about 90 % of the conventional cultivation in the open field [3].

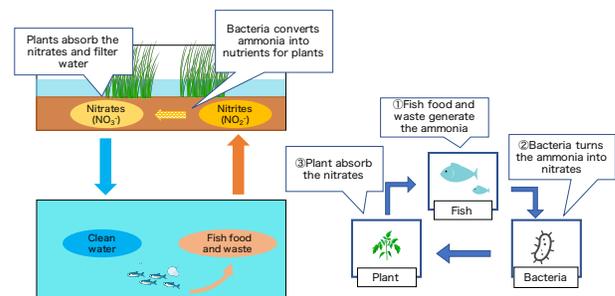


Fig. 1. Overall view of the Aquaponics

Existing study on aquaponics proposes a remote monitoring system of environmental information utilizing multiple sensors [5]. However, it is necessary for the field manager to visually check the growth condition of the fish and the plants because the system is not equipped with a function to automatically observe the growth condition.

Therefore, in this study, we propose a new aquaponics support system using sensor network technology that can automatically estimate the growth condition of the plants and the fish. This system not only measures the environmental information such as water quality composition and temperature but also has the ability to quantify the growth of plants and fish. In order to accurately measure the growth of fish and plants, two different depth cameras are used depending on the environment, and image recognition using deep learning technology is used to accurately estimate the growth.

II. RELATED WORKS AND OBJECTIVES OF OUR STUDY

A. Management System for Aquaponics

In the existing study on an environmental observation system for aquaponics, Paul (2019) et al. propose a system that measures the various environmental information (e.g., pH, temperature, and dissolved oxygen) and automatically controls actuators so that the environmental condition is within an appropriate range for the growth of the plants and the fish [6]. In addition, Zheng (2019) et al. propose a control method of the actuators based on the observation results of the growth environment and reduce the power consumption to 42.9% of the previous system by efficiently operating the actuators [7].

These existing studies use ultrasonic distance sensors to measure the height of plants and evaluate the relationship between the number of growing days and the growth condition of the plants. On the other hand, the method cannot accurately quantify the degree of growth because it measures only the height of the plants. In order to accurately quantify the growth status of plants, it is necessary to estimate the leaf area, which is closely related to the amount of harvest. In addition, the field manager should manually observe the growth condition of the fish in the existing system. The existing distance sensor-based method cannot be applied to the observation of the fish in the water because the infrared ray and the ultrasonic used for measuring the distance cannot travel straight through the water.

B. Image Recognition Using Deep Learning for Growth Estimation of the Plants

Xiaoyang (2019) et al. propose the growth condition estimation system for cucumbers grown in greenhouses. The system acquires RGB images of cucumbers and uses deep learning-based image analysis method, MaskR-CNN, to detect pixels corresponding with cucumbers in the images [4]. By using the MaskR-CNN, the area of the target can be stably estimated by mitigating the effect of the shadow or brightness even in a place where a lot of sunlight enters such as a greenhouse. On the other hand, the method targets only a part of the plants (e.g., fruit) and cannot observe the growth condition of the entire plants including stems and leaves. Therefore, it cannot be applied to leafy vegetables that are mainly grown in aquaponics.

C. Objectives of Our Study

Existing studies aim to realize a system to measure and visualize the environmental information for aquaponics, and have not been able to accurately estimate the growth condition of the plants and fish. By quantifying the growth condition, it can be confirmed whether the interaction among fish, plants, and bacteria in aquaponics is accurate or not, which may improve the efficiency of the aquaponics. Therefore, in this study, we propose and develop a new sensing system that can accurately quantify the growth condition of plants and fish, and clarify the relationship between the growth condition and the state of the growing environment measured by various sensors. In particular, the proposed system is equipped with a method for estimating the growth of fish living in the water to realize practical and efficient aquaponics. The estimation method uses a stereo camera which can observe the three-dimensional structure of the target by analyzing the parallax between multiple visible light cameras even if the target is the fish living in the water where the conventional measurement method using the distance sensor cannot be leveraged. In addition, the MaskR-CNN is used to accurately identify the pixels corresponding with the target from the images captured by the multiple cameras.

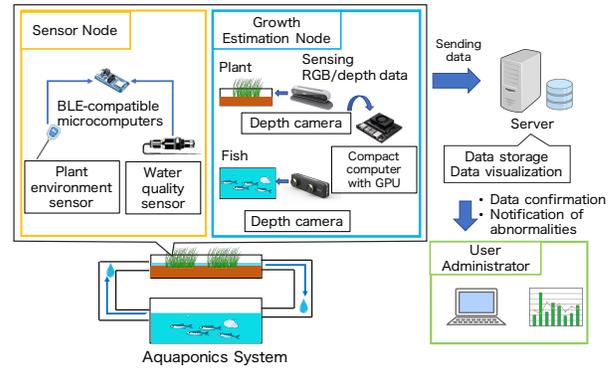


Fig. 2. Overview of the proposed system

III. PROPOSED MANAGEMENT SYSTEM FOR AQUAPONICS

A. Overview of Our Proposed System

Figure 2 shows an overview of our proposed system. As shown in this figure, the proposed system consists of sensor nodes, a growth estimation node, and a management server.

The sensor node measures the environmental information of the aquaponics system using multiple sensors, and transmits the data of the measurement results to the growth estimation node using BLE (Bluetooth Low Energy). The growth estimation node uses two types of depth cameras connected to a small computer to acquire depth images and RGB images of plants and fish. For the growth estimation node, the depth camera using the infrared ray and the stereo camera are utilized to estimate the growth condition of the plants and the fish, respectively. In addition, the growth condition is estimated by analyzing the images in the growth estimation node and only the estimation results are sent to the management server so that the amount of data sent to the management server can be greatly reduced. The management server stores and visualizes the data received from the growth estimation node, and the system operator can remotely check the various statuses of the aquaponics through a web application provided by the server.

B. Design of Sensor Node

The sensor node for measuring the environmental information of the aquaponics is configured using an Adafruit Feather nRF52840 Express, a microcomputer that supports short-range wireless communication via BLE. The system configuration of the sensor node is shown in Fig. 3. To observe the water quality, a pH sensor (pH Kit), a dissolved oxygen sensor (Dissolved Oxygen Kit), and a water temperature sensor (PT-1000 Temperature Kit) manufactured by Atlas Scientific are connected to the sensor node. By measuring the amount of dissolved oxygen in the water, the system operator can check whether the amount of oxygen is enough for the fish or not. The measured pH can be used to check whether the bacteria are correctly converting ammonia contained in fish excrement into nitrate because pH changes based on the amount of ammonia and nitrate in the water. In addition, in order to observe the condition of the environment where the plants

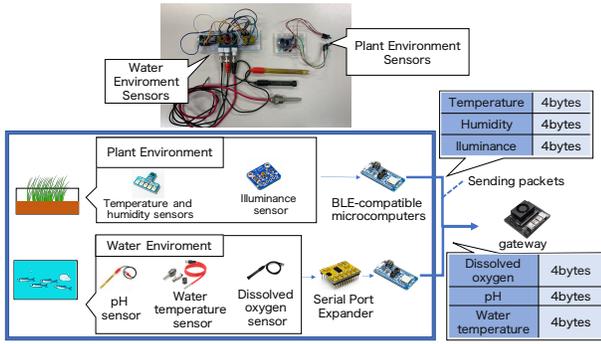


Fig. 3. Device configuration of sensor node

grow, the sensor node consisting of an illuminance sensor (Adafruit TSL2561) and a temperature/humidity sensor module (Adafruit Sensirion SHT31-D) is installed. The sensor node measures the environmental information every 30 seconds and transmits the measured data to the growth estimation node that acts as a gateway, using BLE. Each data measured by the sensor is a floating point number consisting of 4 bytes, and two types of packets are transmitted from the sensor nodes. The first type of packet is consisting of pH, dissolved oxygen, and water temperature data, and the second type is consisting of illumination, temperature, and humidity data.

C. Design of Growth Estimation Node

The growth estimation node is composed of the single board computer, Jetson Xavier NX, and multiple depth cameras. In the following sections, the procedures of estimating the growth condition of the plants and the fish are explained.

1) *Estimation of the Growth Condition of Plants:* In this study, the surface areas of leaves and stems are estimated as the growth condition of the plants. In order to measure the areas, a depth camera module (Real Sense D415 manufactured by Intel Corporation) is utilized to acquire RGB and depth images of the plants. The depth camera transmits the infrared ray to the target and each pixel of the depth image represents the distance between the depth camera and the part that reflects the ray. In order to estimate the growth condition of the plant, RGB and depth images are obtained hourly and the estimation procedure of the growth condition is performed. After that, the estimation result is sent to the management server. The detailed procedure for estimating the leaf area is described in Section IV-A.

2) *Estimation of the Growth Condition of Fish:* The depth camera using the infrared ray (i.e., Real Sense D415) cannot accurately measure the distance to the target in the water because the attenuation of the infrared ray in the water is much higher than that in the air. Therefore, in order to estimate the growth condition of the fish living in the water, the stereo camera (ZED Mini manufactured by Stereolabs) is utilized to measure the three-dimensional structure of the target based on the parallax between multiple visible light cameras. In order to install the stereo camera in the water to take images of the fish, the camera is sealed in an IP68 grade waterproof container as

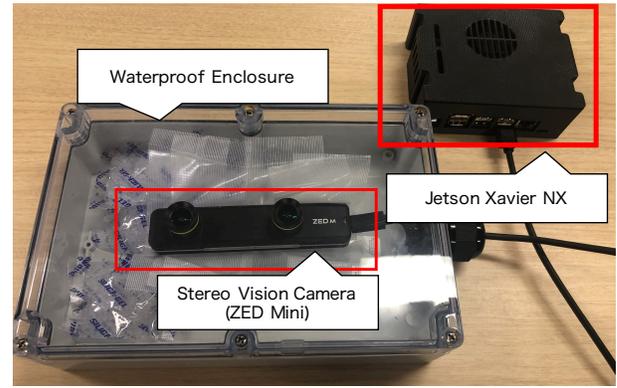


Fig. 4. Waterproof enclosure for depth camera



Fig. 5. Procedure for extracting plants areas

shown in Fig. 4 and is connected to the single board computer through a USB cable. The detailed procedure for estimating the size of the fish is described in Section IV-B.

IV. ESTIMATION METHOD OF FISH/LEAF GROWTH USING DEPTH CAMERAS

A. Growth Estimation Method for Plants

In this study, the proposed method quantifies the growth condition of the plants by estimating the leaf area through the analysis of RGB and depth images acquired by the depth camera. The growth estimation node acquires RGB and depth images of 1280×720 pixels hourly. In order to estimate the growth of the target plants, the pixels corresponding with the target are extracted from the RGB and the depth images and the area of the target is calculated by analyzing the extracted pixels of the images.

1) *Extraction of Plants Regions:* The procedure for extracting the pixels corresponding with the plants from the captured images is shown in Fig. 5. First, the method extracts only the foreground part by comparing the predetermined threshold (e.g., 40 cm) with each pixel of the depth image. In the next step, the RGB value of each pixel in the foreground part is converted to the HSV value and only the green part of the pixels are identified. HSV is a method of expressing color using three elements (e.g., hue, saturation, and lightness). By converting to the HSV values, the extraction of the specific color can easily be performed. The proposed method focuses on the hue and lightness elements of the HSV values and the pixels with a hue within the range of $30 \sim 100$ and a lightness within the range of $40 \sim 255$ are determined as the pixels where the plants are captured.

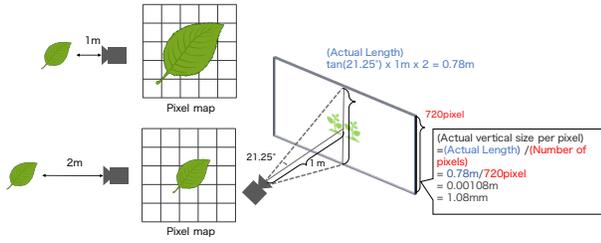


Fig. 6. Estimation of actual area of pixels

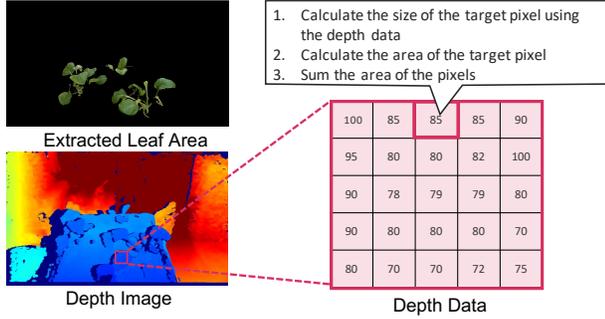


Fig. 7. Estimation of leaf area

2) *Estimation of Leaf Area:* The proposed method estimates the area of the leaf by analyzing the pixels extracted from the RGB and depth images through the previous procedure. Each pixel in the depth image indicates the distance to each part of the target, and the actual area of the part can be calculated based on the viewing angle of the camera and the distance. As shown in Fig. 6, when the distance between the camera and the part of the target changes, the actual area of the leaf corresponding with the single pixel changes. The depth camera (Real Sense D415) used in this study has a horizontal viewing angle of 69.4° and a vertical viewing angle of 42.5° when the shooting resolution is set to 1280×720 pixels. According to the setting, it is possible to estimate the area of the single pixel from the distance. As an example, if the distance between the camera and the object is $1m$ and the vertical viewing angle is 42.5° , the vertical extent of the shooting range is $0.78m$. Since this shooting range consists of 720 pixels in the vertical direction, the actual length of the pixels can be calculated to be about $1.08mm$. Finally, the area of the leaf is calculated by summing up the estimated area of the pixels as shown in Fig. 7.

B. Growth Estimation Method for Fish

1) *Definition of Growth Condition of Fish:* In this study, body height and standard length are defined as metrics of the growth condition of the fish. When measuring the metrics, only the body part is focused without including the tail and the caudal fin. In general, these parts of the fish are damaged due to various reasons, hence the total length of the same individual may vary if these parts are considered to estimate the size of the fish. Therefore, by measuring only the body part, the growth condition can stably be estimated.

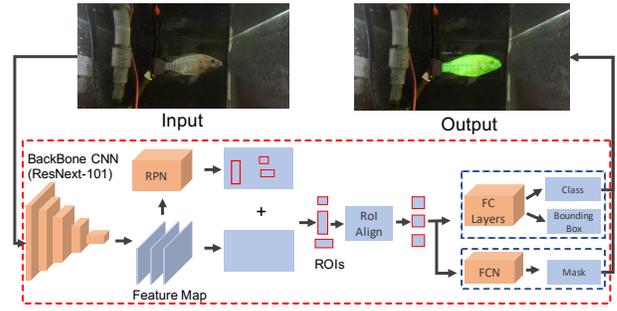


Fig. 8. Structure of the learning model of MaskR-CNN

2) *Construction of a Learning Model for MaskR-CNN:* In this study, we use MaskR-CNN proposed by He et al. to extract pixels including parts of the fish from the RGB images as well as to identify each pixel as an individual fish [8]. By inputting the RGB images into a learning model that has been trained using supervised data prepared in advance, the pixels corresponding with each fish can be output. The network model proposed in this system is shown in Fig. 8.

The learning model is constructed using images taken by a depth camera (i.e., stereo camera) from June to July 2021, and the targets of the images are three tilapias living in the aquarium of an aquaponics system installed in the laboratory where the authors belong. In this experiment, 500 RGB images are captured at different times of the day and are saved in JPEG format with 1280×720 pixels. In addition, an image annotation tool, COCO Annotator, is used to set the correct label to the pixels that contain the fish [10]. Examples of the annotation are shown in Fig. 9.

In order to build the learning model that can handle various states of the fish, the training data includes images that are captured in various situations where the fish stays in different postures and multiple fish are overlapping. From the total of 500 images, 300 images are used for training and 100 images are used for testing to build the learning model. The remaining 100 images are used for validation to evaluate the learning model. In this study, the training of the learning model is performed based on the pre-trained model by using the COCO dataset in order to reduce the processing time and the amount of data required for the training [9]. The COCO dataset is large-scale object detection, segmentation and captioning dataset published by Microsoft.

In this study, a ResNeXt-101 proposed by Xie et al. is used as a template of the learning model [11]. The ResNeXt-101 is a type of convolutional neural network consisting of 101 layers and achieves high prediction accuracy and short execution time. Examples of the estimation results by the learning model are shown in Fig. 10. As shown in this figure, the model can accurately identify the pixels corresponding with the fish even when the fish is swimming at various angles in the water.

3) *Estimation of Body Height and Standard Length:* In the proposed method, the contours of the pixels corresponding with the fish estimated by MaskR-CNN in the depth image are used to obtain the body height and the standard length that

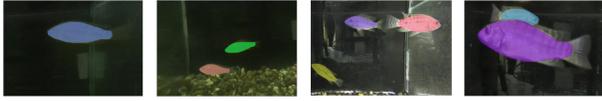


Fig. 9. Examples of annotation of fish



Fig. 10. Examples of detection of fish

are defined as the metrics of the growth condition as shown in Fig. 11. In order to calculate these metrics, an actual length of each pixel should be calculated from the distance data included in the depth image. The median of the distance data in the region corresponding with the fish is used as the representative distance for the instance in order to mitigate the adverse effect of the measurement error of the distance. The representative distance should carefully be decided because there are many reasons that incur the measurement error such as bubbles in the water and light reflection on the water surface. By using this representative distance, the reference length of each pixel is determined.

After that, the line segments corresponding with the body height and the standard length of each instance are extracted from the RGB image. The shape of the group of pixels corresponding with each instance identified by the MaskR-CNN is similar to an ellipse, hence the proposed method derives the bounding rectangle of the ellipse and treats the width and the height of the rectangle as the line segments of the standard length and the body height, respectively. Finally, it is possible to calculate the standard length and the body height by multiplying the reference length.

V. PERFORMANCE EVALUATION OF PROPOSED SYSTEM

A. Estimation Accuracy of Growth Condition of Plants

An experimental evaluation is conducted to evaluate the effectiveness of the proposed method for estimating the growth condition of the plants. The target of the growth estimation is a Japanese mustard spinach growing in the aquaponics system in the laboratory where the authors belong, and the leaf area measured manually is compared with the estimation result

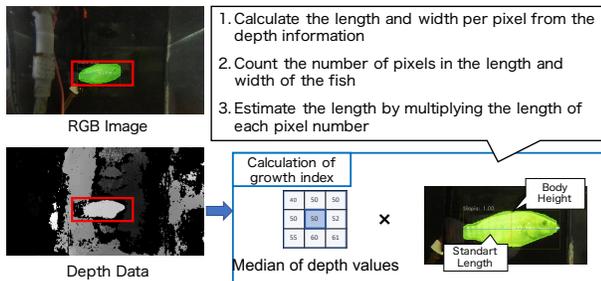


Fig. 11. Procedure of estimation of body height and standard length

TABLE I
EVALUATION RESULT OF THE GROWTH CONDITION ESTIMATION OF THE PLANTS

ID	correct value (cm ²)	Average of the estimation results (cm ²)	RMSE	RMSPE (%)
1	251.9	251.44	2.16	0.86
2	24.5	22.45	2.19	8.96
3	78.25	82.73	4.83	6.16
4	69.38	77.77	9.14	13.2
5	59.0	59.25	3.14	5.43

TABLE II
NUMBER OF DETECTED LABELS FOR EACH CATEGORY

	GT	TP	FP	FN	Recall	Precision
IoU=0.50	196	192	17	4	0.980	0.919
IoU=0.75	196	187	24	9	0.954	0.886
IoU=0.80	196	174	37	22	0.888	0.825

using the proposed method. For the evaluation, five leaves of different sizes are prepared and the leaf area of each leaf is estimated five times. As the performance measure of the estimation accuracy, we use RMSE (Root Mean Squared Error) and RMSPE (Root Mean Squared Percentage Error). Table I shows the evaluation results. As shown in this figure, the average RMSE of the estimation results of the proposed method is 6.92%. Therefore, we can conclude that the estimation accuracy of the growth condition of the plants by the proposed method is sufficiently high to observe the transition of the growth condition with the growing days.

B. Estimation Accuracy of the Pixels Corresponding with the Fish

To evaluate the effectiveness of the proposed method for estimating the growth condition of the fish, we evaluate the estimation accuracy of the pixels in the RGB images corresponding with the fish using the MaskR-CNN. The estimation accuracy of the learning model of the MaskR-CNN is evaluated using the 100 images including 196 fish prepared in advance. In this evaluation, we use the IoU (Intersection over Union) which is a measure of how accurately the pixels of the target are detected as a measure of the estimation accuracy of the proposed method. Based on the IoU, the Average Precision (AP) is derived to evaluate the reliability of the object detection by considering the relationship between the recall and the precision [12]. In this study, we evaluate the number of detections (True Negative, False Positive, False Negative) for each label and AP_{50} , AP_{75} , and AP_{80} are evaluated.

The evaluation results are shown in Tabs. II and III. As shown in these tables, the AP becomes 0.827 even when the threshold of the IoU is set to 0.8 (i.e., AP_{80}), which indicates that the fish can be detected with high accuracy. In order to improve the accuracy, we need to further increase the training data for building the learning model.

TABLE III
FISH IMAGE RECOGNITION ACCURACY

AP_{50}	AP_{75}	AP_{80}
0.962	0.921	0.827

TABLE IV
PERFORMANCE EVALUATION OF FISH GROWTH ESTIMATION SYSTEM

	Body Height	Standard Length
Correct Value	3.2(cm)	8.2(cm)
Average of the Estimation Results	3.21(cm)	7.76(cm)
RMSE	0.101	0.504
RMSPE	3.14(%)	6.15(%)

C. Estimation Accuracy of Standard Length and Height of Fish

In the experimental evaluation, the measured value of the standard length and height of the tilapia is compared with the estimation result. The estimation of the growth condition is performed for one hour, and the 137 estimation results are collected. The estimation accuracy is evaluated by RMSE and RMSPE. The estimation accuracy of the growth condition of the fish is shown in Tab. IV. As shown in this table, the error of the estimation is 3.14% for body height and 6.15% for standard length, which indicates that the proposed method can estimate the growth condition of the fish with high accuracy.

D. Observation Experiment Using the Proposed Method

Using the proposed method, we observe the changes in the growth rates of plants and fish and confirm that we could accurately obtain the changes in growth rates. Fig. 12 shows the relationship between the number of growing days and the estimation result of the leaf area. In addition, Fig. 13 shows the relationship between the number of growing days and the estimated size of the fish. These results show that our proposed system can clarify the growth condition of plants and fish with the passage of the growing days.

VI. CONCLUSION

In this study, we have proposed and implemented a system for estimating the growth of plants and fish to support

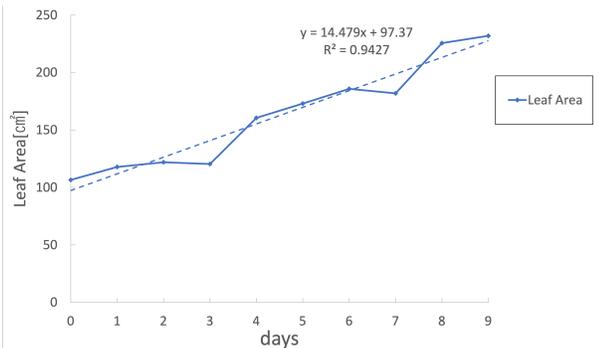


Fig. 12. Observation results of leaf area

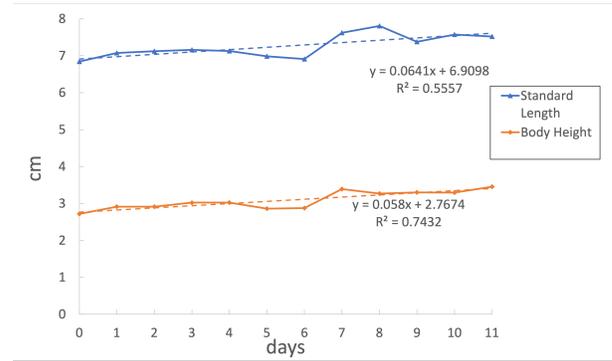


Fig. 13. Observation results of fish

aquaponics operations. The proposed method can automatically measure the size of fish in the water by using a stereo camera and deep learning technology. In the performance evaluation of the system, we have shown that the proposed method can estimate the growth rate of both plants and fish with high accuracy. In addition, we confirmed that we can visualize the growth trend by long-term observation using the proposed method.

In the future study, we will conduct further long-term observations using the proposed system to investigate the effects of the environment on the growth condition.

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