Method of Budding Detection with YOLO-based Approach for Determination of the Best Time to Plucking Tealeaves

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***Abstract*—Method of budding detection with YOLO (You Only Look Once) for determination of the best time to plucking tealeaves is proposed. In order to get the best quality and quantity of tealeaves, it is very important to determine the best time to plucking date. It is most likely that the number of days elapsed after the budding of the tealeaves are the most effective for determine the best plucking day. Therefore, method for detect the budding is getting much important. In this paper, YOLO-based object detection is proposed. Hyperparameter of the YOLO has to be optimized. Also, a comparative study is conducted for the resolution of the cameras used for acquisition of tealeaves from a point of view for learning performance of YOLO. Through experiments, it is found that the proposed method for detection of budding is effective in terms of learning performance for getting the best quality and quantity of tealeaves harvested.**

***Keywords*—Budding; YOLO; plucking; tealeaves; quality; quantity; hyperparameter; learning performance**

I. INTRODUCTION

Plucking is the final step in cultivating tea plants, and it is the task that requires the most attention, as the appropriateness and skill of plucking directly affects the yield of fresh tealeaves and the quality of tealeaves.

Quality and yield are inversely related because the tea is harvested while the buds are still growing. If the harvesting time is delayed, the yield will be higher, but the quality will be lower. In addition, the main components, such as caffeine, catechin, and amino acids (theanine), gradually increase as the new shoots grow, but as the leaves harden and the core buds stop forming, they rapidly decrease, and crude fiber increases. This will lead to a decrease in quality. Therefore, it is important to determine the picking time that will ensure a high yield while maintaining good quality, and this is also the optimal time for picking.

The best time to pick tealeaves is when the degree of opening[1] is 70% and four to five leaves are open. The open degree is defined as shown in Fig. 1. Two examples of tealeaves show the opening degree of around 25 degrees. Also, there is “not open” tealeaf (it is called as bud) at the top right portion of Fig. 1.

The optimum time for plucking is when the percentage of new buds with cores fixed is 50-80%. The knowledge about the relations between the best timing of plucking and the opening degree are as follows,

1) Where the opening degree: The percentage of buds whose cores have stopped. 50-80% is appropriate,

2) Opening: The tea buds should fully open and not grow any further,

3) Core: The undeveloped tip of a bud,

4) The number of leaves open: Four to five leaves for the first picking tealeaves, and about four for the second and the third picking tealeaves.

The optimal time is when the tealeaf buds are fully opened and no longer elongate. Common tealeaf is made by picking the fourth or fifth tealeaf from the tip. The technique for picking tea is called “one heart and two leaves”, which means picking the topmost heart leaf of a new bud and the two tealeaves below.

Fig. 1. Definition of the open degree of the tealeaves.

In order to get the best quality and quantity of tealeaves, it is very important to determine the best time to plucking date. It is most likely that the number of days elapsed after the budding of the tealeaves are the most effective for determine the best plucking day. The method for the most appropriate plucking date determination based on the elapsed days after sprouting with NIR reflection from Sentinel-2 optical sensor data is proposed and validated already. The problem situated here is

[1] A new tealeaf (new buds) is born with two tealeaves without open. In accordance with tealeaves growing, two leaves are opening gradually.

how to detect the sprout. It is still difficult to detect the sprout even for visual perception. The dates of sprout are different from each other famers. It is necessary to determine the sprout date objectively. Therefore, only thing we have to do is to determine the tealeaves sprouting date so that a method for detect the budding is getting much important. In this paper, YOLO-based object detection is utilized for determination of sprouting date.

The following section describes research background with related research works followed by proposed method. Then some experiments are described followed by conclusion with some discussions.

II. Research Background and Related Research Works

A. Research Background

Tealeaf is a crop that is plucked while the new buds are growing, and the yield and quality change depending on the time of plucking. Yield and quality are inversely proportional, and the timing of picking must be adjusted to balance the desired yield and quality. The basic information about the best time and suitable time for picking tealeaves is as follows.

The number of times a year is harvested is often two times, the first and the second, or the three times, including fall and winter bancha (the third picking tealeaves). Ichibancha[2] picking is at its peak from late April to May in many tealeaves producing regions. Plucking takes place on the 88th night, the 88th day counting from the first day of spring (2023 February 4th). Compared to the second and later tealeaves, the first-class tealeaves have less catechin and caffeine, which cause bitterness, and much amino acids, which contribute to "umami" (tasty) and sweetness, resulting in a refreshing taste. If tealeaves are picked early, the yield will be low, but it will be able to harvest young, high-quality buds. Conversely, if the picking time is delayed, the yield will increase, but the stems and lower leaves will harden, and the quality of the rough tea will decrease. Since the yield is low when the tealeaf quality is at its best, the best time to pick is two to three days after the time when the quality is at its best. There are various ways to properly assess this period.

1) Generally speaking, farmers often judge the harvesting season by "feeling" the fruit. To objectively judge this, the "degree of opening" is used. A flag tealeaf appears at the end of a new bud's growth, and the bud that has stopped growing is called an "emerging bud". E: emergence degree is the percentage of appearance of emerging buds relative to the total number of buds within a certain area.

E=the number of emerging buds/the total number of buds (1)

In the case of hand-picking, the picking period usually occurs when green tealeaves are 60-70% and black tea is 40-50%. In the case of mechanical picking, it can exceed 90%.

2) Pick an average of about 5 newly opened tealeaves from the base, hang a weight from the tip, measure the length from the base to the top of the curved part, and calculate the ratio to the length of the new sprout. Hardening degree can be expressed as follows,

H=bending length from the base/total bud length (2)

The optimum time for picking is first-brown tealeaves with a degree of hardening of 40-60%. Paying attention to the length of the buds, it is said that it is appropriate to pick buds of 10 cm for the first-class tealeaves, and 6-7 cm for the second and the third tealeaves, and 5-6 cm.

3) Measure the number of newly opened tealeaves, and the best time to pick them is when the average number of open leaves is around 4 for the first tealeaves, and around 3.5 for the second tealeaves. On average, it takes about five days for one leaf to open for the first tealeaves, and about four days for the second and the third tealeaves. By estimating the number of tealeaves that have developed after the tealeaf opening stage and calculating the number of days required, the approximate suitable time for picking can be estimated.

All of these methods are subjective and intuitive and cannot objectively and stably determine the optimum harvesting time. Therefore, the proposed method is required to realize an appropriate plucking date determination method by using a time series of camera acquired imagery data.

B. Related Research Works

There are the following previously reported research results relating to the tealeaves characterization approach,

Method for estimation of grow index of tealeaves based on Bi-Directional reflectance function: BRDF measurements with ground-based network cameras is proposed and validated [1]. Also, wireless sensor network for tea estate monitoring in complementally usage with Earth observation satellite imagery data based on Geographic Information System (GIS) is proposed [2]. On the other hand, method for estimation of total nitrogen and fiber contents in tealeaves with ground-based network cameras is proposed [3]. Meanwhile, Monte Carlo ray tracing simulation for bi-directional reflectance distribution function and grow index of tealeaves estimations is conducted [4].

Fractal model-based tea tree and tealeaves model for estimation of well opened tealeaf ratio which is useful to determine tealeaf harvesting timing is created [5]. The method for tealeaves quality estimation through measurements of degree of polarization, leaf area index, photosynthesis available radiance and normalized difference vegetation index for characterization of tealeaves is proposed [6]. On the other hand, optimum band and band combination for retrieving total nitrogen, water, and fiber in tealeaves through remote sensing based on regressive analysis is investigated [7].

Appropriate tealeaf harvest timing determination based on NIR images of tealeaves is conducted [8] together with appropriate harvest timing determination referring fiber content in tealeaves derived from ground based NIR (Near Infrared) camera images [9]. Meanwhile, method for vigor diagnosis of tea trees based on nitrogen content in tealeaves relating to NDVI (Normalized Difference Vegetation Index) is proposed [10].

[2] First picked tealeaves are called "Ichibancha"

Also, cadastral and tea production management system with wireless sensor network, GIS-based system and IoT technology is created [11]. On the other hand, method for determination of tealeaf plucking date with cumulative air temperature: CAT and photosynthetically active radiation: PAR is proposed [12].

Meantime, YOLO and learning method related research works are reported as follows,

YOLO-based automatic target Aimbot in first person shooter games is reported with system implementation [13]. On the other hand, initial assessment of deep learning-based daytime clear-sky radiance for VIIRS (Visible/Infrared Imager and Radiometer Suite) is conducted [14]. Meanwhile, unmixing method for hyperspectral data based on sub-space method with learning process [15]. Meantime, a new approach of probabilistic cellular automata using vector quantization learning for predicting hot mudflow spreading area is proposed [16].

Visualization of learning process for back propagation Neural Network clustering is proposed [17]. On the other hand, Question Answering for collaborative learning with answer quality prediction is created [18]. Meanwhile, Pursuit Reinforcement Competitive Learning: PRCL-based online clustering with tracking algorithm and its application to image retrieval is proposed [19] together with PRCL-based on-line clustering with learning automata [20].

Interactive m-learning media technology to enhance the learning process of basic logic gate topics in vocational school and engineering education is introduced [21]. On the other hand, emotion estimation method with Mel-frequency spectrum, voice power level and pitch frequency of human voices through CNN (Convolution Neural Network) learning processes is proposed [22]. Meanwhile, category decomposition based on subspace method with learning process is proposed [23]. On the other hand, an approach for on-line clustering is proposed [24]. Furthermore, pursuit reinforcement competitive learning is proposed as an approach for on-line clustering [25].

III. Proposed Method

Developing technology to identify germination date from images. Currently, the cultivation area is large, and the sprouting date of each field is not known. Also, there are only a limited number of people who can judge the germination date. If the sprouting date can be determined, the optimal time for picking tea leaves can be objectively and stably estimated based on the number of days that have passed since sprouting. In other words, it is necessary to judge the germination date and formulate an efficient harvesting plan. Furthermore, as shown in Fig. 2, it has been confirmed that it is effective to predict the index value from the cumulative post-emergence temperature.

The legends in Fig. 2, Yabukita, Meiryoku, Fushun, Sayamamidori, and Okumidori are species of the tealeaves plucked. 1000kg/10a means the yield of the tealeaves.

The image was taken to capture the inside of a 20 x 20 cm frame (4032 x 3024 pixels), compressed (896 x 672 pixels), and annotated (see Fig. 3), and the sprouting rate was determined. The equipment used for imaging was an iPhone13Pro, and the image size was 896 x 672 pixels (see Fig. 4). We tried to increase the number of buds in the image, but the bud size decreased. From these, we selected the training data (see Fig. 5).

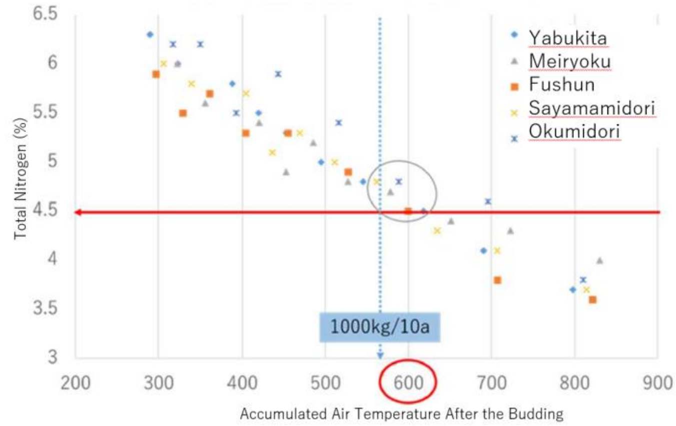

Fig. 2. Relation between total nitrogen content in plucked tealeaves and accumulated air-temperature after the budding.

Fig. 3. Acquired photo image of the tealeaves with 20 by 20 cm^2 frame.

Fig. 4. Tealeaves image which includes buds.

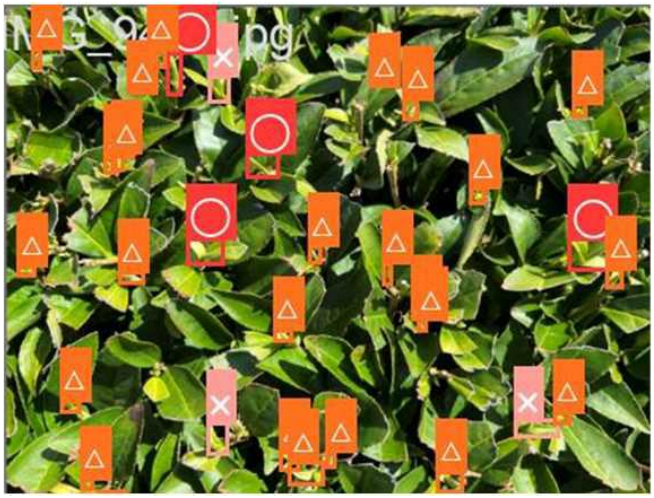

Fig. 5. Training data for YOLOv8 (○：budding、×：non-budding、△：non-adopted buds).

By creating a model with YOLOv8, we were able to make predictions from images by running the code below on Google colaboratory. YOLOv8 is downloaded and installed as follows,

```
pip install ultralytics
```

Then mount the Google Drive as follows,

```
from google.co.colab import drive
drive.mount('/gdrive')
```

After that, the code for estimating sprouting rate through inference using model, which is stored in the Google Drive as follows,

```
!yolo detect predict model="/gdrive/MyDrive/datasets/yolov8/best0109.pt" source ="/gdrive/MyDrive/datasets/yolov8/tests" conf=0.25 iou=0.45 imgsz=640 save=True.
```

IV. Experiment

The sprouts in the image were classified into three classes: budding, non-budding, and other, and the sprouting rate was determined. We thought that judging the budding rate by the ratio of budding to non-budding would be closer to determining the actual budding date.

We selected 40 images for learning and 10 images for verification. mAP50 was adopted as the learning performance. A portion of training images are shown in Fig. 6. As a result, it was found to be 0.376. At this time, the number of labels in the verification image was ○: 41 ×: 54 △: 254, and we thought that by answering △ for sprouts, the model would improve accuracy.

The classification was changed to two classes: ○: budding ×: non-budding, and other sprouts were not labeled. We thought that this would improve the accuracy of detecting new shoots. As shown in Fig. 7, budding can be labeled much clear than before. In this case, YOLOv8 is used for object detection of learning processes.

When learning performance was evaluated using 200 images for training and 50 images for verification, mAP50 = 0.502, indicating that although the accuracy improved, it was not possible to capture sprouted buds. At this time, the number of labels for verification was ○: 215 ×: 262.

In order to pad the training data, the images were flipped upside down and the amount of training data was doubled. At this time, 200 sheets for training and 50 sheets for verification were changed to 400 sheets for training and 100 sheets for verification as shown in Fig. 8. We also ensured that the same buds were given the same label.

When 400 images were used for training and 100 images were used for verification, mAP50 was 0.506. At this time, the number of labels for verification was ○: 414, ×: 540. From this, although no change was observed in the mAP50 score, it is thought that it became possible to detect sprouted buds. At this time, it was confirmed that the precision of sprouting improved to 0.351 when using 200 sheets for training and 0.569 when using 400 sheets for training. The number of labels in the training images was ○:1621、×:1838 as shown in Fig. 9.

Fig. 6. A portion of training images.

Fig. 7. Example of detected buddings using YOLOv8.

(a) Original image. (b) Up-side down of image.

Fig. 8. Up-side-down of the original training image for augmentation of training samples.

(a) Poor number of training samples. (b) Twice many numbers of training samples.

Fig. 9. Although no change was observed in the mAP50 score, it became possible to detect sprouted buds (○：1621、×：1838).

At this time, the number of learning times (epochs) was 139, and the best score at the 89th time was precision: 0.569 ×: 0.456 and recall: ○: 0.587 ×: 0.418. We also confirmed that the number of learning sessions remained almost flat after 40 times of the number of epochs. The learning performance is shown in Fig. 10.

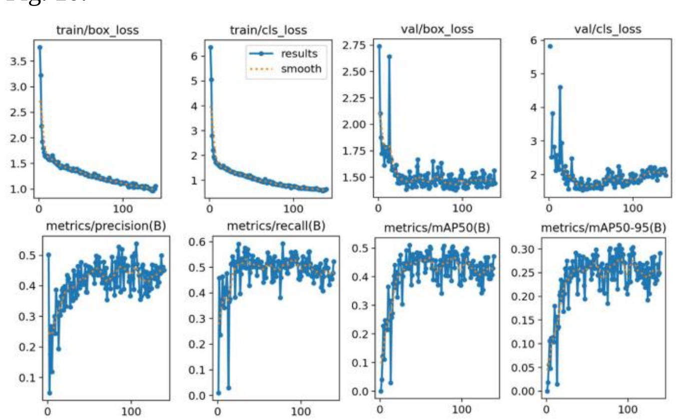

Fig. 10. Learning performances.

Training and validation loss functions are shown in good shape for both of bounding box and classification at around beyond 100 of epochs. Precision and recall are not so stable enough though.

V. Conclusion

Method of budding detection with YOLO for determination of the best time to plucking tealeaves is proposed. In order to get the best quality and quantity of tealeaves, it is very important to determine the best time to plucking date. It is most likely that the number of days elapsed after the budding of the tealeaves are the most effective for determine the best plucking day. Therefore, a method for detect the budding is getting much important. In this paper, YOLO-based object detection is proposed. Hyperparameter of the YOLO has to be optimized. Also, a comparative study is conducted for the resolution of the cameras used for acquisition of tealeaves from a point of view for learning performance of YOLO.

Through the experiments, it was found that the smaller the size of the sprout in the image, the more difficult it was to detect. Therefore, it was found that it was necessary to devise ways to set the camera resolution and the distance to the observation target. We also found that setting boundaries between different labels was difficult. Furthermore, by creating a model using YOLOv8, it has become possible to easily predict the sprouting rate with high accuracy.

When we check quality of the tealeaves harvested at the confirmation of the sprouting date which is determined by using visible camera data based on YOLOv8, it is confirmed that the quality of the harvested tealeaves is very good. Therefore, it is the proposed method is validated and useful for determination of appropriate plucking day.

VI. Future Research Works

We plan to verify the difference between the actual sprouting rate and the sprouting rate predicted by AI. Furthermore, in order to improve detection accuracy, it is necessary to further increase the amount of training data. Furthermore, we plan to verify the accuracy using images taken with IoT cameras, etc. in the near future.

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