Method for Tea Leaf Plucking Timing Prediction with High Resolution of Images Based on YOLO11

Kohei Arai[1], Yoho Kawaguchi[2]
Information Science Department, Saga University, Saga City, Japan[1]
Oita Prefecture Agriculture, Forestry and Fisheries Research and Guidance Center, Oita City, Japan[2]

***Abstract*—As a method for estimating the time when tea leaves reach their peak quality (amino acid content) (optimum picking time), our previous study revealed that the optimum picking time is when the accumulated temperature from the detection of germination of new buds reaches 600°C. However, the accuracy of this germination detection was insufficient, so the estimation accuracy of the optimum picking time was also insufficient. Since annotation accuracy is extremely important for germination detection by YOLO11, strict attention is paid to annotation by hand and by increasing the number of training datasets. The detection accuracy has been improved compared to the germination detection by YOLOv8, which was previously proposed and used relatively low-resolution images. The conclusion of this study is that the estimation method of the optimum picking time based on the criterion that the optimum picking time (amino acid content reaches its peak) is effective when the accumulated temperature from germination detection meets the condition of 600°C. The effectiveness of this method has been confirmed by comparison with germination detection by experts. For tea farmers, being able to predict the optimum picking time, when the amino acid content in the new buds is at its peak, is important, and we are sure it will have a positive impact on agricultural researchers studying this subject.**

Keywords—Tealeaf plucking; YOLO; budding detection; spatial resolution; optical image; annotation; germination rate

I. Introduction

The quality of tea leaves is greatly affected by the time of plucking, so it is important not to miss this timing. The method of deciding the time of plucking tea varies depending on the climate and variety of the year, but it is generally decided based on an index called "degree of opening". A new bud has 5 to 6 leaves that are the origin of the bud, and as it grows, it gradually opens. This last leaf is called the "flag leaf", and when it opens, it is said to have "opened". The percentage of new buds that have opened out of the total number of buds in a certain area is called the "degree of opening", and it is said that plucking is optimal when this percentage is 50 to 80%. In addition, if you pick early, you can also pick when it is 30 to 50%.

The time of plucking is closely related to the quality and yield of the green leaves. After the tea leaves sprout, the sprouts grow and reach their peak in amino acids (tea leaves contain amino acids such as theanine, glutamic acid, aspartic acid, arginine, and serine. These amino acids work together to create the umami and sweetness of tea) and this is when the optimum time for picking is reached. Once the optimum time for picking has passed, these amino acids are transformed into catechins because of sunlight, which is fine for functional catechin tea, but makes it unsuitable for high-quality sencha. For this reason, we check the time when the buds sprout. The program's output is either germinated or not. To determine this, we use YOLO11 to analyze the captured images and estimate the optimum time for picking. Meanwhile, when the softness and umami components of the new buds are at their peak, the new buds have not yet grown sufficiently, and the yield is low. On the other hand, when the yield is at its peak, the "degree of opening" is too high, so the leaves become hard and astringent. For these reasons, it is best to pick the tea leaves when there is a certain yield, and the quality does not deteriorate too much. The timing of picking greatly determines the quality of the tea leaves that year.

To improve the profitability of tea production, it is important to increase the gross profit from the first harvest, which accounts for approximately 80% of the profit from the tea produced annually. Gross profit from tea is calculated by multiplying the yield by the unit price, and although the unit price is influenced by the market price at the time, it is generally determined by the quality. In other words, the main factors that determine the profitability of a tea plantation are the yield and quality of the tea leaves harvested, and increasing both in a balanced manner contributes to improving profitability. For this reason, tea plantation management increases productivity while ensuring a certain level of quality is maintained at production sites.

Previously, the method of budding detection based on YOLOv8 [1] (You Only Look Once version 8) with a relatively low spatial resolution of images for the determination of the best time to pluck tea leaves was proposed. We have already reported that if tea leaves are picked when the accumulated temperature from the time of tea leaf budding reaches 600°C, good quality tea leaves can be harvested in large quantities. Therefore, a method for detecting the budding is getting much more important. In this study, a method based on YOLO11 (You Only Look Once version 11) of object detection with relatively high spatial resolution of images is proposed. Also, a comparative study is conducted for the resolution of the cameras used for the acquisition of tealeaves from a point of view for learning performance of YOLO11. Furthermore, a comparison was made between the tea leaf germination date determined by experts and the AI-predicted germination date, and it was confirmed that the prediction accuracy was high.

Through the experiments, it was found that smaller the size of the sprout in the image, the more difficult it was to detect. Therefore, it was found to be 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 YOLO11, it has become possible to easily predict the sprouting rate with high accuracy.

The following section describes related research works, followed by methods and procedures for a comparative study between the previous method and the current method with relatively high spatial resolution of optical images and a comparatively highly accurate learning model. Then some experiments are described, followed by a conclusion with some discussions.

II. RELATED RESEARCH WORKS

In the following related research studies, the effects of stratification, temperature, and light on seed germination of tea plants are clarified [2]. These effects are essential components for tea plant health conditions. Meanwhile, modeling the budburst phenology of tea plants is proposed [3]. The bud-burst phenology is getting more important for global issues. On the other hand, germination and storage of tea seeds are discussed [4]. Germination issues are the concerns with this study.

Analysis of climatic factors affecting the phenology of tea (*Camellia sinensis*) in eastern China is well reported [5]. NIST3254 is the information provided by NIST: *Camellia sinensis* (green tea) leaves. Climatic factors must be considered for the germination of tea plants. Meanwhile, the effects of cold stratification on seed germination in tea plants (*Camellia sinensis*) are cleared [6]. On the other hand, the variation of seed germination and seedling growth of tea (*Camellia sinensis*) collected from different altitudes of the Darjeeling hills under water stress conditions is clarified [7].

Genetic variation and differentiation in tea (*Camellia sinensis*) germplasm using RAPD markers are discussed [8]. The genetic diversity, relationship and molecular identification of fifteen well-known, widely planted traditional Chinese elite tea genetic resources [*Camellia sinensis* (L.) O. Kuntze] preserved in the China National Germplasm Hangzhou Tea Repository in the Tea Research Institute of the Chinese Academy of Agricultural Sciences, located in Zhejiang province, China, were investigated using RAPD markers. Meanwhile, estimation of first-flush sprouting time of tea shoots using a thermal time model is well reported [9]. On the other hand, the germination behavior of tea seeds under different environmental conditions is discussed [10].

Genetic diversity and geographical differentiation of cultivated tea in China by AFLP markers are discussed [11]. Based on the AFLP method, AFLP Figures were obtained in Guangdong tea plants. In this study, in total, 365 bands were amplified by 5 pairs of primers and 73 bands were amplified by each primer pair on average; a total of 338 (92.6%) polymorphic AFLP markers were detected. Meanwhile, the prediction of tea shoots harvesting time by monitoring environmental factors and shoot growth is proposed [12]. On the other hand, growth models for tea shoots are also proposed [13].

Predicting the flush development time of tea using environmental factors is proposed [14]. Meanwhile, a dynamic model for predicting the growth and development of the tea shoot is proposed [15]. On the other hand, the effects of temperature on seed germination in tea are clarified [16].

A machine vision system for automated tea shoot detection is developed [17]. Meanwhile, seed germination and early growth of tea (*Camellia sinensis* L.) as influenced by temperature is cleared [18]. On the other hand, image-based tea bud detection using deep learning approaches is proposed [19].

The method for plucking date determination based on the elapsed days after sprouting with NIR (Near Infrared) reflection from Sentinel-2/MSI (Multi-Spectral Imager) data is proposed [20]. It is equipped with a high-resolution multispectral imager and will carry out an optical mission with the primary objective of observing land areas. It forms a constellation of two identical satellites (Sentinel-2A, 2B). Meanwhile, appropriate tealeaf harvest timing determination based on NIR images of tealeaves is discussed [21]. On the other hand, a method for vigor diagnosis of tea trees based on nitrogen content in tealeaves relating to NDVI (Normalized Difference Vegetation Index) is proposed [22]. NDVI is an index that indicates the distribution and activity of vegetation and is the ratio of NIR and red-light reflectance (NDVI={NIR-RED}/{NIR+RED}). NDVI is expressed as a normalized value between -1 and 1, and the denser the vegetation, the higher the NDVI value.

Cadastral and tea production management system with a wireless sensor network, a GIS (Geographical Information System) based system and IoT (Internet of Things) technology is developed [23]. Methods for the determination of tealeaf plucking date with Cumulative Air Temperature (CAT) and Photosynthetically Active Radiation (PAR) are proposed [24]. PAR designates the spectral range (wave band) of solar radiation from 400 to 700 nanometers that photosynthetic organisms can use in the process of photosynthesis. This spectral region corresponds to the range of light visible to the human eye. Photons at shorter wavelengths tend to be so energetic that they can be damaging to cells and tissues, but are mostly filtered out by the ozone layer in the stratosphere. Photons at longer wavelengths do not carry enough energy to allow photosynthesis to take place.

On the other hand, the method of budding detection with a YOLO-based approach for the determination of the best time to pluck tea leaves is proposed and validated with actual data [1].

These studies cover various aspects of tea leaf budding estimation and germination rates, including the effects of environmental factors like temperature, light, and stratification on seed germination and budburst phenology. They also include modeling approaches for predicting budburst and studies on genetic variation affecting these processes.

On the other hand, the following studies are noticeable for object detections,

1) Foreign Object Detection in Urban Rail Transit Based on Deep Differentiation Segmentation Neural Network [25].

2) Multi-pose face recognition method based on improved depth residual network, International Journal of Biometrics [26].

3) Facial micro-expression recognition method based on CNN and transformer mixed model, International Journal of Biometrics [27].

III. Proposed Method

A. Proposed Method for Determination of Appropriate Plucking Time Estimation

The proposed procedure for the determination of appropriate plucking time estimation is shown in Fig. 1. To create a YOLO11-based learning model for bud detection, tea leaf canopy images are acquired with a high resolution of a visible camera, together with precise annotations of buds manually. High resolution of images is highly required at this stage. When performing object detection with low-resolution images, detection errors occur because high-resolution images of sprouts cannot be obtained. Therefore, in this study, we narrow the instantaneous field of view and take images with improved resolution to increase the number of pixels per sprout. After that, budding detection at the tea farm areas concerned with a newly acquired tea leaf canopy image based on the learned YOLO11 is made for the determination of germination date. At this stage, the date of germination is when 70% of the tea leaves are detected to have germinated. The optimum time for harvesting is when the accumulated air temperature from the germination date reaches 600℃. Air temperature is available from the meteorological agencies around the world.

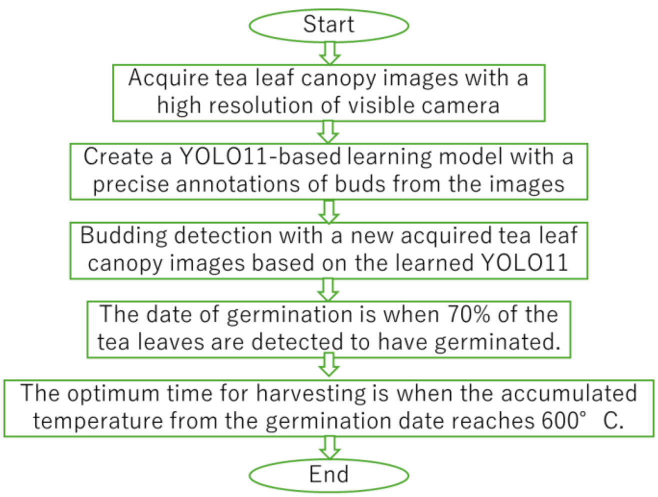
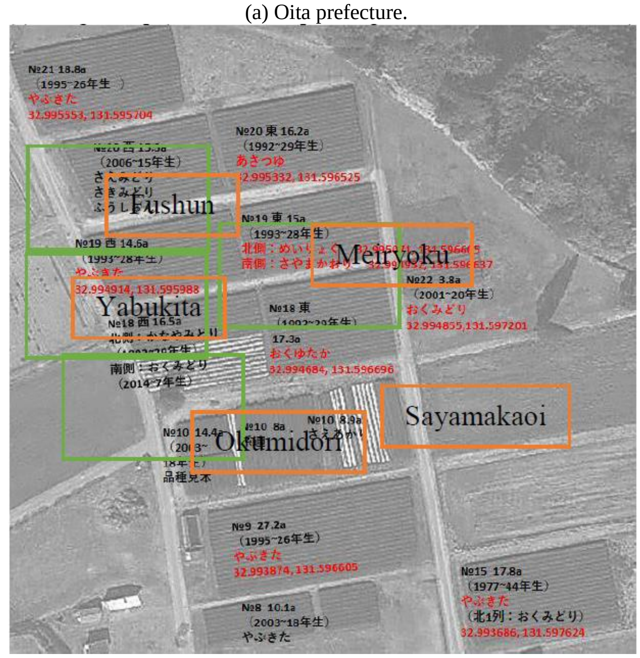


Fig. 1. Proposed procedure for determining an appropriate plucking date.

B. Research Background and the Previous Methods for Comparison

We have already shown that it is effective to predict tea component values from the accumulated temperature after germination [1]. The purpose of this research is to develop technology to identify the germination date from images. Currently, the cultivation area is large as shown in Fig. 2, and the germination date of all tea fields is not known, but the aim is to establish a method to make this possible and to identify the best time to record tea leaves from the germination date and accumulated temperature. In other words, a method to determine the germination date is necessary for efficient picking planning. There is an experimental tea farming area in which five species of tea trees (Oku-midori, Fushun, Sayama-Kaori, Meiryoku, and Yabukita) are planted.

(a) Oita prefecture.



(b) Test sites.

(c) Google photo.

Fig. 2. Location of the test site for five species of tealeaves in the intensive study area of Bungo-Ono, Oita, Japan.

The intensive study area is situated at Oita Prefectural Agriculture, Forestry and Fisheries Research Center, Bungo Ohno in Oita Prefecture, Japan (32.99 N, 131.59 E). The institute is established by Oita prefectural local government for promoting agriculture, forestry and fisheries as well as training and guidance of farmers and fishermen. There is an experimental tea farming area in which several species of tea trees (Oku-midori, Fushun, Sayama-Kaori, Meiryoku, and Yabukita) are planted. The tea tree Okumidori, which is the basis of sencha, is a breed made by crossing Yabukita, Yabu-kita and Shizuoka Zairai No. 16, and it reaches its season after Yabukita. It is characterized by its mild taste and low bitterness. It is also attracting attention as tencha (a raw material for tencha and matcha) and gyokuro. Okumidori tea tree has many buds, so you can expect a large yield.

In Fushun, which has a slightly upright tree, if the spacing between plants is 60 cm and the row spacing is changed from the customary 50 cm to 25 or 60 cm, the annual yield of fresh leaves will decrease. In the case of Fushun, when the row spacing is 50 cm, the annual fresh leaf yield decreases when the plant spacing is increased from the conventional 60 cm to 75 cm, and the planting density is reduced to 80% of the conventional planting density (1481 plants/10a). Sayamakaori is characterized by its strong aroma.

The tea leaves demonstrate enhanced firmness and a more desirable shape relative to Yabukita tea. Because it contains a lot of catechins, which are tannins, the tea has a strong and astringent taste. The plucking period of Meiryoku is the same as or slightly earlier than that of Yabukita, and the tree is vigorous and grows vigorously. Four or five years after planting, the total yield of first and second tea leaves is relatively high. The quality is the same as or slightly better than that of Yabukita. It is suitable because it is rather strong. One of the characteristics of "Yabukita" is its strong cold resistance. It is resistant to red wilt, blue wilt, and frost damage. It is also characterized by good rooting and is highly adaptable to various soils. Another strength in terms of growth is that the roots and shoots are uniform and grow quickly, making it easy to replant. For this reason, it is highly rated by farmers as an easy-to-grow variety.

C. The Proposed Method

In a previously published study [24], we clarified a method for estimating the germination date from images taken periodically from directly above the tea tree canopy as shown in Fig. 3. Namely, a 20 x 20 cm frame was placed on the tree canopy surface and a photograph was taken so that the new buds within the frame were visible. The captured image was then compressed to fit YOLO's reading size (640 pixels) to create training data. The first version of YOLO was released in 2015 and revolutionized the field of object detection. This model is characterized by being faster than previous methods by processing the image at once.

In 2016, YOLOv2 was released, improving accuracy and speed. This version improved the network structure and strengthened the ability to detect smaller objects. In 2018, YOLOv3 appeared, introducing multi-scale prediction, enabling the detection of even smaller objects. This version significantly improved the accuracy of object detection. And from 2020 onwards, YOLOv4, YOLOv5, and the latest YOLOv10 each version has been released, continuously improving efficiency and accuracy. YOLOv10 incorporates the latest technology and optimizes the balance between accuracy and speed of object detection. In this research, YOLO11 is used for budding detections.

YOLO is becoming the standard for object detection due to its high speed and accuracy. Throughout its development history, technology has continued to evolve and is expected to be used in various application fields. One such field is agriculture, where it is used to monitor the health of crops and detect pests, making farming more efficient. In this study, it is used to detect new tealeaf buds.

Fig. 3. Example of the acquired image of the tea tree canopy with a relatively low-resolution camera.

Then the annotation of buds was performed as shown in Fig. 4.

Fig. 4. Example of the annotated buds (〇denotes “bud”, ×denotes “not bud”).

However, the resolution of the camera used was insufficient, which resulted in insufficient accuracy in estimating the germination date, and therefore, insufficient annotation accuracy, and insufficient detection accuracy based on the YOLOv8 object detection learning model. Therefore, in this study, we carried out the following three measures (updating the teacher data and object detection algorithm) to improve the accuracy of estimating the germination date.

1) Improved the resolution of the training data.
2) Improved annotation accuracy.
3) Changed to the latest YOLO model.

As a result, the precision rate was 0.512, the recall rate was 0.518, and the mAP50 was 0.506, which means that the learning performance was not sufficient. In addition, the size of the buds was small, and it was particularly difficult to detect unsprouted buds, so we determined that it was necessary to improve the camera resolution.

To maintain the resolution by dividing the image, we decided to prevent preprocessing into a 640 pixels square by padding at the top and bottom while maintaining the aspect ratio when the image is a horizontal rectangle. Therefore, we cropped both ends of the captured image to make it square, divided it (5 pixels by 5 pixels) to match the reading size of YOLO, and created training data as shown in Fig. 5.

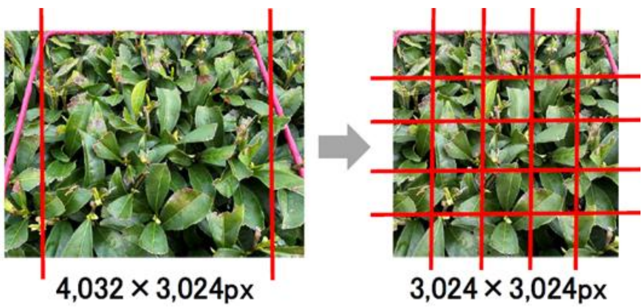


Fig. 5. Example of the acquired image with 640 pixels square and divided images with 3024 by 3024 pixels of resized images.

Then the annotation of buds was performed as shown in Fig. 6.

Fig. 6. Example of 640 by 640px of the annotated buds (Blue colored rectangles).

D. Improvement of Annotation Accuracy

YOLO11 is a model that boasts extremely high accuracy and speed in object detection. To maximize its performance, proper data annotation is essential. Annotations provide the "correct answer data" for the model to learn, and play the following important roles:

1) Accurate learning. Annotations allow the model to understand which parts are objects and improve its ability to recognize them accurately. For example, by drawing a bounding box around an object in an image, the model learns the location of the object.

2) Mitigating bias. Through annotations, you can identify misrecognition of specific classes and correct the bias of the model. This allows for fairer and more accurate predictions.

3) Domain specialization. By annotating data related to the project, the model will have recognition capabilities specialized for a specific domain. This allows it to perform well in specific applications.

The method of data annotation for YOLO11 learning is as follows:

1) Data collection. First, collect images and videos containing the target object. This data will be the basis for the model to learn. Selection of annotation tools: For annotation work, we use tools such as LabelImg[1] and Roboflow[2]. These tools provide the function of drawing bounding boxes for images and specifying the class of objects.

2) Annotation work. For the collected data, we draw bounding boxes for each object and assign the corresponding class label. This work can be done manually, but it can be made more efficient by using an automatic annotation tool.

3) Preparation of data format. YOLO11 requires annotation data to be saved in a specific format (such as YOLO PyTorch TXT format). This allows the model to read the data correctly.

4) Data verification. To ensure that the annotation is accurate, we perform reviews by others and automatic checks. This allows us to improve the quality of annotation.

5) Model training. We use the annotated dataset to train the YOLO11 model. After training, it is important to evaluate the performance of the model and correct the annotation if necessary.

Therefore, annotation is a key factor in the performance of YOLO11 training. Accurate annotation allows the model to detect objects with higher accuracy. Using the right tools and methods to perform effective annotation is the key to success. As stated in https://github.com/jsbroks/coco-annotator, when evaluating annotation accuracy, we aim to improve annotation accuracy by using annotation results output according to the COCO format. The research results of this study are that we have improved the resolution of the captured images, used object detection by YOLO11, and demonstrated that germination detection by improving annotation accuracy is effective for estimating the optimum time to pick tea leaves.

In comparison between YOLO11 and YOLOv8, YOLO11 not only improves accuracy (mAP) compared to YOLOv8, but also shows advantages in terms of computational efficiency and hardware requirements. The main points of comparison are summarized below. Computational efficiency and performance comparison,

[1] https://github.com/HumanSignal/labelImg

[2] https://github.com/roboflow/auto-annotate

1) Reduction in number of parameters and FLOPs

YOLO11n: 2.6M parameters / 6.5B FLOPs vs. YOLOv8n: 3.2M / 8.7B

YOLO11x: 56.9M parameters / 194.9B FLOPs vs. YOLOv8x: 68.2M / 257.8B

2) Improvement in CPU inference speed

YOLO11n: 56.1ms vs. YOLOv8n: 80.4ms (30% faster)

YOLO11x: 462.8ms vs. YOLOv8x: 479.1ms

3) Performance in GPU environment. No significant difference between the two models in the T4 TensorRT10 environment (e.g., YOLO11n 1.5ms vs. YOLOv8n 1.47ms)

For each tea variety, we randomly photographed the location and performed annotations. In this case, depending on the shooting angle, it may be difficult to determine whether the image is budded or not, so the labels may not be accurate. To avoid this situation, in this study, we performed annotations by taking photos from a fixed point. Examples of typical sprouting processes are shown in Fig. 7. This makes it possible to capture changes in each bud, eliminating human-made labeling errors and improving learning accuracy.

(a) Not sprouted.

(b) Sprouting Date: 3 days later.

(c) Sprouting completely.

Fig. 7. Examples of sprouting process.

As an annotation method for YOLO, we imposed the condition that there must be no space between the object and the box as shown in Fig. 4. In addition, by changing the training data from resized images to segmented images, we thought that it would be possible to closely surround each bud, which would improve the accuracy of the labels.

E. Improvement of Learning Model (YOLO)

We use YOLO11, which is faster to calculate and more accurate than YOLOv8, as shown in Fig. 8, to improve accuracy. YOLO11 is designed for speed, accuracy, and ease of use, making it ideal for a wide range of object detection and tracking, instance segmentation, and more. Open a command prompt (terminal) in C:\python\python312 and create a virtual environment. Set the environment name to YOLO11 and run python -m venv yolo11 to enter the virtual environment. Make sure YOLO11 is displayed and set it to C:\python\python312\yolo11\Scripts\activate. Proceed with installing the libraries in a virtual environment. The official website is https://github.com/ultralytics/ultralytics. You can include all libraries by installing YOLO11 with the pip command "pip install ultralytics".

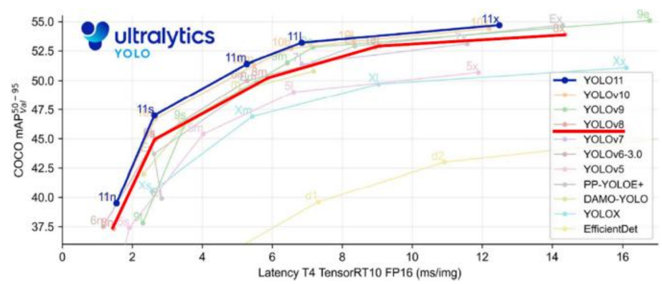


Fig. 8. YOLO11 is superior to YOLOv8.

Open the project folder in VS-Code by running mkdir c:\yolo11. Switch the interpreter to the virtual environment and execute the training by writing the same thing in Python as in the command prompt above. Data settings are done using a YML file, with the data arranged as shown below,

```
C:/yolo11/datasets/my_datasets
    |        ├──── images
    |        |     └──── train
    |        |     └──── val
    |        └──── labels
    |              └──── train
    |              └──── val
    |
    └──── my_datasets.yaml
```

It was first released in 2015, it is a cross-platform, meaning it is available for Windows, macOS, and Linux. Visual Studio Code is lightweight yet powerful, offering many features such as debugging, version control, and extension support. It is especially popular among developers of various programming languages, including JavaScript, TypeScript, Python, and C++.

On the other hand, YML is a data format that represents structured data as a string. It stands for YAML (YAML Ain't Markup Language) and is characterized by its ease of reading and writing. The characteristics of YML are that it is lightweight and easy-to-remember grammar used for writing software configuration files and exchanging data between different software, and it is very easy to use. In addition, line breaks and indentations have clear meanings, and ease of use for programmers is emphasized. It is a complete superset of JSON, another data serialization language, and can do more than just what JSON can do.

YAML is a popular programming language because it is designed to be easy to read and understand and can be used in conjunction with other programming languages. Its flexibility and ease of use make it the language used by Ansible® to create automation processes in the form of Ansible playbooks. YAML has features from programming languages such as Perl, C, XML, and HTML. YAML is also a superset of JSON, so JSON files work directly in YAML. There are no regular formatting symbols such as curly braces, brackets, closing tags, or quotes. YAML files are also easier to read, as they use indentation to determine structure and indicate nesting, just like Python. To maintain portability across systems, tab characters are not allowed by design, so whitespace characters (literal space characters) are used instead.

Now, training can be started. The training results will be automatically saved in the folder runs. The training results will be saved in the weights folder, so just change the YOLO11.pt part of the inference program to best.pt (full path). During training, scaling (scale = 0 to 1, default 0.5) is automatically applied. It is also possible to apply rotation, mixup, learning rate, etc. In that case, just write mixup = 0.5, flipud = 0.5, lr0 = 1E-5, etc. in the model.train section.

IV. Experiment

A. Procedure and Conditions

The test varieties selected were "Yabukita", "Okumidori", "Meiryoku", "Sayamakaori", and "Fushun". These are the five main varieties of drinkable tea. The shooting period was a total of fourteen days from March 26th to April 10th, 2024 (excluding March 30th and April 7th). In addition, in the learning method 5,384 annotation images were created, 3,450 images were used as training data, and 1,360 images were used as validation data. The accuracy was verified using 574 test data. Annotations were performed on 673 images divided from the original image, and the number of annotations was increased by eight times by data expansion (rotation, inversion). Learning settings version: YOLO11s, mixup: 0.5 was used, and the rest were performed with default settings.

B. Learning Performance

Fig. 9 shows the changes in the loss function and evaluation index for each learning iteration. “train” and “val” mean training and validation, respectively. “box” denotes bounding box, “cls” denotes classification, and “dfl” stands for distribution focal loss, respectively. On the other hand, mAP50 means that the mean Average Precision is calculated by a threshold of 50 with IoU (Intersection over Union). As usual, the loss function decreases gradually, and precision and recall as well as mAP, are gradually increasing. Also, the training performance is better than the validation performance (which is much more important than the training performance). From these graphs, 200 of the number of epochs would be enough because performances are saturated at around 200.

The results of the learning model (the training and validation data (○ corresponds to sprouting and × corresponds to non-sprouting) are shown in Table I. These performance results show a significant improvement in accuracy in comparison to previously reported results [1], shown in Table II.

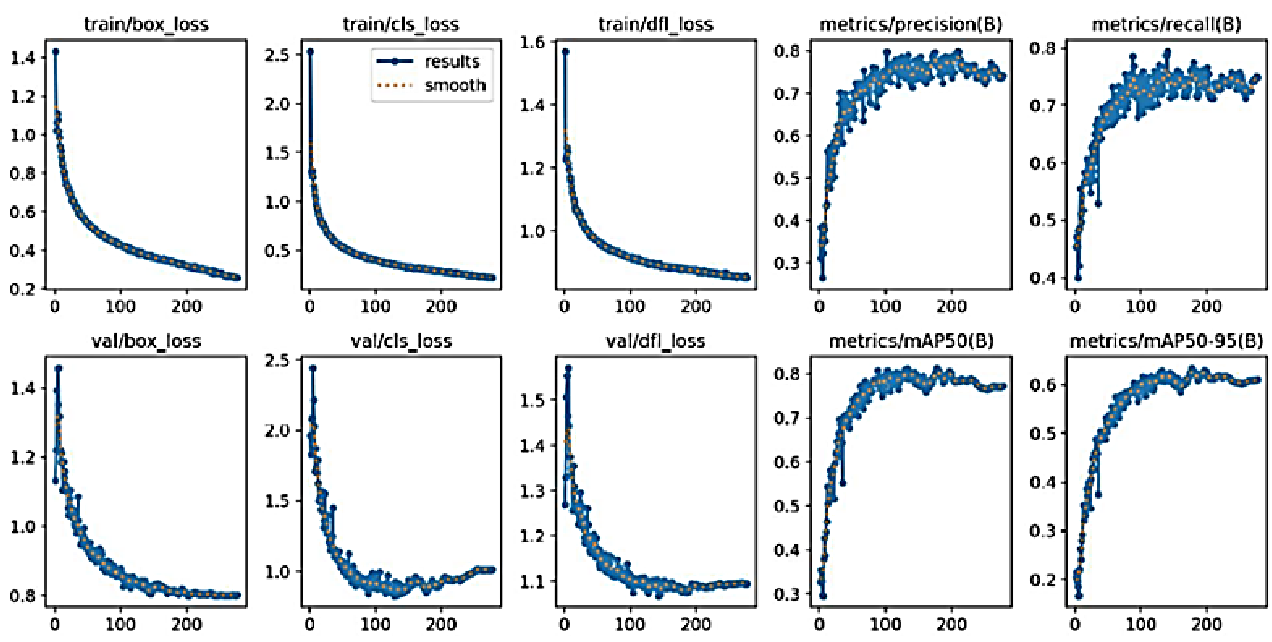


Fig. 9. Changes in the loss function and evaluation index for each learning iteration (horizontal axis is the number of epochs).

TABLE I. TRAINING AND VALIDATION PERFORMANCE OF YOLO11

Precision=0.762	Recall=0.769	mAP50=0.814
○:0.781	○:0.862	○:0.884
×:0.742	×:0.667	×:0.743

TABLE II. TRAINING AND VALIDATION PERFORMANCE OF YOLOV8

Precision=0.512	Recall=0.518	mAP=0.506
○:0.569	○:0.587	○:0.594
×:0.456	×:0.448	×:0.418

Similar results were also obtained with the test data, as shown in Table III.

TABLE III. PRECISION AND RECALL OF LEARNING PERFORMANCE OF YOLO11

Precision	○:0.779	○:0.748
Recall	×:0.748	×:0.704

Therefore, it can be said that the accuracy has improved significantly by 25 to 30%. The best score was achieved at 177 epochs. Fig. 10 shows the number of instances of each class in the training data.

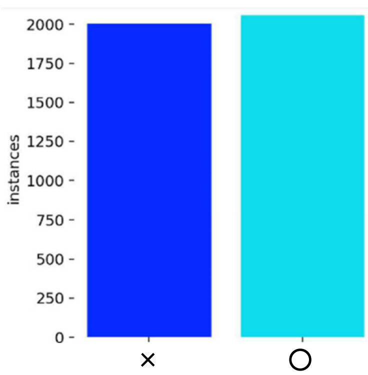


Fig. 10. The number of instances of each class in the training data.

Also, Fig. 11 shows examples of training and validation data. In Fig. 11, ○ corresponds to sprouting and × corresponds to non-sprouting, respectively.

C. Development of a Bud Break Prediction Model Using AI

It is found that bud break can be estimated with the tea leaf images acquired. It is referred to as an AI-based method. Based on the model which we created, we estimate the germination date from the image. The image used for estimation is the image before division (4,032 by 3,024 pixels). This includes the data used for learning.

Two tea field locations of 20 by 20 cm were surveyed for each variety. The bud break date was defined as the day when the proportion of buds that had sprouted reached 70%. Table IV shows the changes in germination rate (the numbers in Table IV show the percentage ratio of bud tea leaf) of each variety.

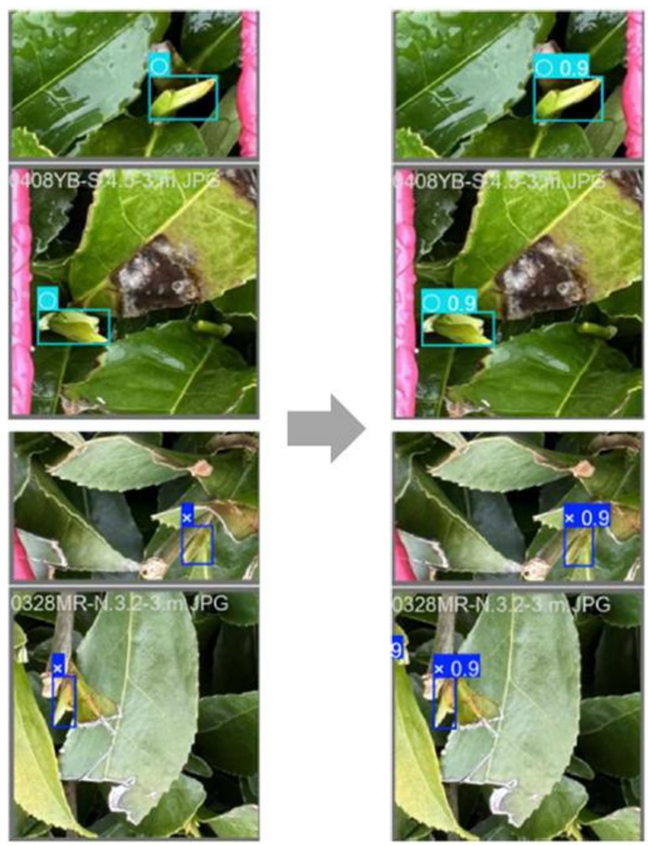
It is obvious that the germination rate is different by the variety. Red colored percentages show the germination rate. Actual denotes the germination rate estimated by the expert while, AI denotes that by AI-based method. As a result, the germination dates were consistent for three of the five varieties, and even in cases where they did not match, the error was just -two days.

From the above results, we believe that using the model we created to predict the germination date from images taken with a smartphone is effective and demonstrates high prediction accuracy.

D. Discussion

The conventional method of estimating the optimum time for plucking tea leaves was based on the experience of tea farmers and was determined by the feel of the new buds on the tea plant, the number of leaves, and the degree of leaf opening, while observing the weather. Scientifically speaking, the best quality tea leaves can be picked when the theanine content of the new buds is at its highest, but measuring this without contact is time-consuming and costly, so an alternative method was needed.

We have determined that the optimum time for plucking is when the accumulated temperature from the buds' germination reaches 600°C and have shown that the germination time of the new buds can be estimated using images captured by a visible camera and YoloV8, an AI-based method for object detection. However, the pixel size of the images and the accuracy of object detection were insufficient, so the accuracy was not sufficient compared to conventional objective methods.



(a) Training Data. (b) Validation Data.

Fig. 11. Examples of training and validation data.

TABLE IV. CHANGES IN GERMINATION RATE OF EACH VARIETY

Meiryoku	Mar.28	Mar.29	Mar.31	Apr.1	Apr.2	Apr.3	Apr.4	Apr.5	Apr.6	Apr.8
Actual	0%	0%	21%	37%	50%	65%	88%	100%	100%	100%
AI	0%	5%	25%	28%	39%	69%	90%	100%	97%	89%
SayamaKaori	Mar.28	Mar.29	Mar.31	Apr.1	Apr.2	Apr.3	Apr.4	Apr.5	Apr.6	Apr.8
Actual	0%	0%	0%	18%	29%	44%	55%	82%	100%	100%
AI	5%	0%	5%	8%	25%	50%	58%	76%	83%	88%
Yabukita	Mar.29	Mar.31	Apr.1	Apr.2	Apr.3	Apr.4	Apr.5	Apr.6	Apr.8	Apr.9
Actual	50%	25%	30%	44%	66%	66%	68%	73%	100%	100%
AI	17%	17%	15%	25%	42%	82%	77%	71%	89%	100%
Fushun	Apr.3	Apr.4	Apr.5	Apr.6	Apr.8	Apr.9	Apr.10	Apr.11	Apr.12	Apr.13
Actual	0%	7%	12%	31%	75%	85%	100%	100%	100%	100%
AI	7%	6%	8%	54%	74%	77%	56%	84%	76%	82%
Okumidori	Apr.3	Apr.4	Apr.5	Apr.6	Apr.8	Apr.9	Apr.10	Apr.11	Apr.12	Apr.13
Actual	12%	33%	58%	61%	58%	77%	87%	100%	100%	100%
AI	27%	37%	53%	59%	81%	65%	79%	78%	94%	88%

In this study, we show that by using images from a visible camera with sufficient pixel size and using YOLO11, which has a higher detection accuracy than YOLOv8, the estimation error of the germination time of the new buds can be reduced within two days.

V. CONCLUSION

We developed a budding detection method using captured images based on YOLO11. The conventional method with YOLOv8, which was proposed by the authors, had a weakness in the accuracy of detecting tea leaf budding. It was insufficient. One of the reasons is that the camera resolution. Also, the budding detection accuracy was not good enough.

By using twice much high-resolution camera and YOLO11 for budding detection with careful annotations, budding detection accuracy is improved remarkably. When the tea leaf germination rate estimated using the proposed method was compared with that of experts, it was found to be in extremely good agreement. It is concluded that the accuracy of YOLO11-based budding detection has improved significantly by 25 to 30% in comparison to the previously reported YOLOv8 [1].

Also, an AI-based method for the estimation of germination rate is proposed. Based on the model which we created, we estimate the germination date from the image. As a result, the germination dates were consistent for three of the five varieties, and even in cases where they did not match, the error was -2 days.

The proposed method is effective for detecting germination of not only the tea varieties targeted in this study, but all other tea varieties. A method based on the criterion that the optimum time for plucking is when the cumulative temperature from the time of germination is 600°C (when the amino acid content reaches its peak) is effective for estimating the optimum time for plucking.

VI. FUTURE RESEARCH WORKS

We plan to validate the proposed AI-based method for germination rate as well as for budding date prediction with the actual tea leaf quality and yield in the future. Also, it would be better to do an estimation of the most appropriate harvest date with deep learning, which can be applied to these estimations.

Further experimental studies are required for further validation of the proposed method for the determination of the most appropriate plucking date for harvesting good-quality new flesh tealeaves (Ichiban-Cha).

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AUTHOR'S PROFILE

Kohei Arai, He received BS, MS and PhD degrees in 1972, 1974 and 1982, respectively. He was with The Institute for Industrial Science and Technology of the University of Tokyo from April 1974 to December 1978 also was with National Space Development Agency of Japan from January, 1979 to March, 1990. During from 1985 to 1987, he was with Canada Centre for Remote Sensing as a Post Doctoral Fellow of National Science and Engineering Research Council of Canada. He was professor of Saga University from 1990 to 2017. Also, he was a Councilor for the Aeronautics and Space related to the Technology Committee of the Ministry of Science and Technology during from 1998 to 2000 and was a councilor of Saga University for 2002 and 2003. He also was an executive councilor for the Remote Sensing Society of Japan for 2003 to 2005. He was the Vice Chairman of the Scientific Committee was an Award Committee member of ICSU/COSPAR during. He is a Science Council of Japan Special Member (COSPAR Committee) since 2012. He is an Adjunct Professor of Nishi-Kyushu University and Kurume Institute of Technology as well as Prishtina International University. He wrote 134 books and published 747 journal papers as well as 585 conference papers. He received 66 of awards including ICSU/COSPAR Vikram Sarabhai Medal in 2016, and Science award of Ministry of Mister of Education of Japan in 2015. He is now Editor-in-Chief of IJACSA and IJISA. http://teagis.ip.is.saga-u.ac.jp/index.html