Estimating When Leaves Turn Yellow and Fall for Tourists via Multimodal Monitoring with IoT Devices

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Abstract— **Japan's complex and varied topography gives rise to distinct seasonal landscapes, which serve as a major attraction for domestic and international tourists. Among these natural phenomena, the autumnal transformation of foliage—particularly the vivid yellowing of ginkgo leaves—holds considerable appeal. However, the phenological timing of leaf senescence and abscission exhibits substantial spatial variability, often leading to visitor dissatisfaction when travel coincides with either the premature stage prior to coloration or the post-abscission phase. To mitigate this issue, we propose a predictive system designed to estimate the timing of autumnal leaf coloration. This system employs Internet of Things (IoT) technologies to collect environmental data, including photographic imagery of ginkgo trees and measurements of solar radiation. The acquired data are then processed to forecast the imminent onset of leaf yellowing and subsequent abscission. A prototype implementation of the system was developed, and its predictive performance was empirically validated, demonstrating its efficacy in estimating key phenological transitions.**

Keywords-Yellow Leaves Tourism; Internet of Things; Artificial Intelligence; Estimating.

I. INTRODUCTION

This paper is an extended version of earlier published work [1]. This paper added a quantitative evaluation of the results when deep learning was not used for image classification, clarifying the effectiveness of using deep learning.

They also made modifications to the definition of the yellowing rate and recalculated the time series analysis, resulting in improved accuracy.

Japan has a rugged landscape and is blessed with a diverse range of flora and fauna. These offer fascinating and unforgettable experiences for many tourists, both from Japan and abroad. Ginkgo trees, with their brilliant golden and vibrant yellow leaves, are a particularly popular tourist attraction. However, the period during which ginkgo trees shimmer in their beautiful golden hue is short. At most, they last about a week, and this period only occurs once a year in the fall. The time when ginkgo leaves turn yellow varies depending on the location. Even in the same location, weather conditions vary from year to year, so the leaves may not turn yellow on a specific day. If tourists visit before the ginkgo trees turn yellow, they will only see the green trees and miss out on the excitement. Even after the leaves have fallen, they will be sad to see them. Knowing when the leaves turn yellow is very important.

Biological seasonal observations [2] are conducted as a systematic approach to observing seasonal changes in various plants and animals, such as the yellowing of ginkgo leaves and the blooming of cherry blossoms. The Japan Meteorological Agency began this observation in 1953 and has covered 34 species and 41 phenomena. Biological seasonal observations rely on visual observation, which poses a challenge due to the enormous human cost involved. The scope of observations is being significantly reduced. It has also been pointed out that in urban environments, shading caused by buildings may affect biological seasonality. However, there is little research on the biological seasonal observation of local plants in urban environments [3][4][5] that could reduce human costs.

To address these challenges, we propose a method that reduces human labor while enabling the detection and prediction of yellowing in specific ginkgo trees within urban environments. First, we developed an IoT device capable of automatically collecting fixed-point photographs of ginkgo trees along with local meteorological data. From the captured images, the number of yellow leaf pixels is extracted to quantify the degree of yellowing. However, the apparent color of ginkgo leaves in images varies depending on factors such as cloud cover, camera performance, and leaf density. Simple pixel-based extraction cannot adequately account for these variations, often misclassifying green or other regions as yellow leaf pixels. To overcome this limitation, we employ deep learning–based color identification that is robust to such image variations. Moreover, recognizing that natural phenomena such as leaf yellowing and leaf fall progress continuously rather than as binary states, we aim to predict ginkgo phenology with higher granularity by extracting indicators representing the degree of yellowing and the extent of leaf fall, and conducting regression analyses using these indicators as objective variables.

This paper is organized as follows: Section II introduces related research. Section III explains the observation data. Section IV explains the observation system built using IoT devices. Section V explains how to analyze the collected observation data. Section VI presents the classification results, and Section VII discusses the prediction of the time when leaves will turn yellow. Section VIII summarizes this paper and discusses future challenges.

II. Related Research

As biological phenological observations have been reduced, various studies on biological phenological observations have been reported to solve the problem. Below, we will discuss research related to the development of biological phenological observation methods.

In Endo et al.'s research [6][7], we proposed a method to estimate the timing of relic season changes in biological phenological observations at low cost from X (formerly Twitter) location-attached posts. By analyzing the names of organisms such as ginkgo and maple in the posts and co-occurring words indicating their location and state, the timing of biological phenological changes was estimated from the frequency of posts. Furthermore, the effectiveness of the proposed method was verified by comparing with observation data from the Japan Meteorological Agency.

In Iha et al.'s research [8], we used post data related to cherry blossoms from March to the end of April 2022 as a dataset and performed time series prediction of the number of posts using machine learning. As a result, we confirmed an improvement in the precision and recall of the time series prediction model of the number of posts compared to conventional methods.

In Ito et al.'s research [9], they developed a robot that can automatically measure plant growth information by utilizing low-cost IoT devices and open source image processing libraries. This robot was used to periodically capture images of spinach growth, demonstrating its potential for application in growth prediction and detection of poor growth.

In a study by Sato et al. [10], multispectral observations using a drone and IoT devices were used to observe the growth status of wheat using vegetation indices.

As described above, many methods have been researched for efficiently observing biological phenologies and plants using SNS(Social Networking Service) and IoT devices, but there has been no research on a system that can estimate the best time for yellow leaves to appear.

There are studies such as Meier et al. [11] and Kim et al. [12] that have attempted to predict the period of leaf yellowing and leaf fall based on long-term observation data from a botanical perspective, but these predictions are not based on data that can be observed using simple IoT devices. These studies rely on expensive observation data, such as human observation, and are different from the goal of this research, which is to develop a system that collects data at low cost and predicts the period of leaf yellowing.

III. Observation Data

Biological phenological observations were performed in accordance with the Japan Meteorological Agency's biological phenological observation guidelines, and fixed-point photography was performed on ginkgo trees at the Polytechnic University as specimen trees (Figure 1). In addition, meteorological information from the surrounding area (hereinafter referred to as sensor measurements) is measured as a feature used to predict the yellowing and falling of ginkgo leaves. The sensor measurements are temperature, humidity, air pressure, carbon dioxide concentration, and illuminance.

Figure 1. Specimen Trees.

Green and yellow leaves are related to photosynthesis. Photosynthesis is greatly affected by illuminance and carbon dioxide concentration. For this reason, in addition to basic sensors such as temperature, we also prepared sensors for illuminance and carbon dioxide concentration for observation.

The measurement sensor needs to be installed near the specimen tree. Because it also requires a power supply, the sensor was installed outside a window of a building near the specimen tree. The ginkgo tree on the far left of Figure 1 is closest to the sensor. However, because this tree reflects light and is prone to casting shadows, the ginkgo tree enclosed in a red frame was used as the specimen tree.

The observation period is from November 1, 2024 to January 10, 2025. The measurement frequency was one image and sensor measurement value set per minute. However, each sensor measurement value was taken for 24 hours, but images were taken only from 6:00 to 18:00. This is because it gets dark after 6pm, making it difficult to determine the color of the leaves. It is possible to take pictures at night using expensive, specialized cameras. However, visual inspection requires personnel costs, so we are trying to use IoT devices to reduce the cost. We avoided using expensive equipment. Furthermore, image data from times when no photography is taking place will be substituted with the last image, i.e., the image taken at 6pm. We did not consider using the next image taken, i.e., the image taken at 6am, because the image data cannot be determined until a photo can be taken the next day at 6am.

IV. Observation System

The configuration of the measurement system is presented in Figure 2. Measurements related to the ginkgo trees are obtained using devices from the M5Stack series. Fixed-point photographs of the trees are captured with a Timer Camera. Temperature, humidity, and atmospheric pressure are recorded using the HAT-YUN module, CO_2 concentration is measured with an SGP30 sensor, and illuminance is measured with a BH1750FVI-TR sensor. All sensor data are collected and processed by an M5Stick microcontroller.

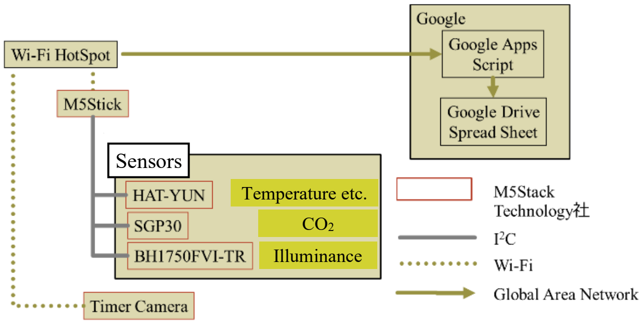

Figure 2. Overview of the observation system and data flow.

Images of the ginkgo trees will be saved to Google Drive and the sensor measurements will be saved to a spreadsheet using a script written in Google Apps Script provided by Google.

V. ANALYSIS METHOD

In preliminary experiments, we performed pixel-by-pixel determination of yellow leaves in acquired images. We defined the green and yellow ranges and classified them into three classes, including the rest. Specifically, the green range was defined as (160, 20, 15) to (210, 55, 50) in HSV, and the yellow range was defined as (36, 15, 30) to (60, 40, 70) in HSV. However, green and yellow leaves shine due to reflected light and do not fall within the predetermined green and yellow ranges. Conversely, shadows sometimes resulted in actual green or yellow leaves that also did not fall within the predetermined green and yellow ranges. We manually reviewed 5,000 images that did not fall within the yellow or green range of HSV. 13.5% were green leaf images and 9.6% were yellow leaf images. This indicates a 20% or greater chance of misclassifying leaves as green or yellow due to glare or shadows. Conversely, we manually reviewed 5,000 images that fell within the yellow or green range of HSV. 16.2% were not green or yellow, but were recorded as green or yellow due to glare or shadows. In other words, determining the green and yellow ranges in advance does not accurately determine green or yellow leaves. Therefore, we used machine learning to classify images into three classes using the following procedure.

Furthermore, we defined the yellowing and fallen leaf rates. From the acquired image, an area that only contains ginkgo leaves (hereafter, ginkgo image) is cut out. Furthermore, the ginkgo image is divided into 10x10 pixel images (hereafter, square images), and each square image is classified into "green", "yellow", and "other". The classification method is to first select only ginkgo images at times when the illuminance, one of the sensor measurement values, is between 1000 and 10000 lux. These images are divided into square images and labeled as "green", "yellow", and "other". These square images are used as learning data for training, and a model is generated that classifies the images into three classes: "green", "yellow", and "other". When an image containing only ginkgo leaves is divided into 10x10 pixels using this model, the number of images classified into each class is counted (Yellow Classification Count : y, Green Classification Count : g). In calculating the index, the ratio of the number of yellow class classifications to the total number of green and yellow class classifications (hereafter referred to as leaf amount), which indicates the entire ginkgo leaf, is defined as the "yellow leaf rate," Eq. (1) and the "fallen leaf rate" Eq.(2) is defined as the rate at which the leaf amount at the time of measurement has decreased from the maximum leaf amount obtained up to the time of measurement (hereafter referred to as maximum leaf amount : max(y + g)).

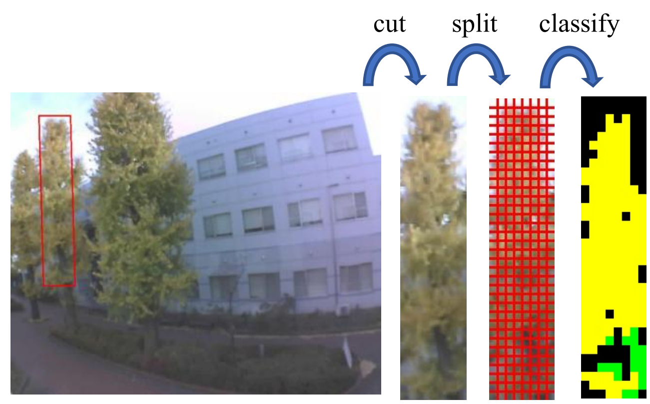

Figure 3. Learning and Classification Flow.

In earlier published work [1], we used the leaf yellowing rate given by Eq. (1). This is a natural definition, as it is the percentage of yellow leaves. However, it changes when leaf fall begins. When leaf fall begins, not only does the number of yellow leaves decrease, but the leaf amount also decreases. Therefore, if we use the yellowing leaf rate in Eq.(1), the value will change abnormally large when leaf fall begins. It is even possible for the yellowing leaf rate to increase even though the number of yellow leaves is decreasing. This has a negative impact on time series estimation. Time series estimation in earlier published work also did not achieve high accuracy. Therefore, we will modify the definition to Eq.(3), which can accurately represent the change in the decrease in yellow leaves after leaf fall begins. In this study, we recalculated using the yellowing leaf rate in Eq.(3).

$$\text{Yellow leaf rate (old)} = \frac{y}{g+y} \times 100[\%]\ . \quad (1)$$

$$\text{Fallen leaf rate} = \left(1 - \frac{g+y}{\max(g+y)}\right) \times 100[\%]\ . \quad (2)$$

$$\text{Yellow leaf rate (new)} = \frac{y}{\max(g+y)} \times 100[\%]\ . \quad (3)$$

According to the observation conditions of ginkgo in the biological phenology observation of the Japan Meteorological Agency [2], the yellow leaf day refers to the first day when the majority of the leaves have turned yellow when viewed as a whole and almost no green parts are visible. The defoliation day refers to the first day when approximately 80% of the leaves of the specimen tree have fallen. Therefore, the leaves are judged to be yellow when the yellow leaf rate is 80% or more of the maximum leaf amount, and the leaves are judged to be fallen when the defoliation rate is 80% or more.

Multivariate time series prediction is performed using LightGBM. If we can tell from camera images that the leaves are turning yellow or starting to fall, it will lead to a reduction in human costs. However, tourists need more information. What will the yellowing of the leaves be like in the next few days? When will the leaves start to fall? Information like that. For this, time series forecasting is necessary. Accuracy is verified using the yellow leaf rate and defoliation rate as the objective variables, and sensor measurements and processed data from them as explanatory variables.

VI. Classification Results and Discussion

The results of three-class image classification using the image classification model ResNeXt are shown below. The three classes are yellow, which means yellow leaves, green before the leaves turn yellow, and other colors, which mean fallen leaves. Evaluation data was classified using the model determined to be the best by generalized k (k=5)-fold cross-validation, and the evaluation results shown in Table I were obtained. According to Table I, the precision rate for the green class classification is a little low at 0.892. However, all other colors were above 0.92. We counted the number of areas that were green, yellow, and other colors in the ginkgo image, and we believe that we were able to calculate the indices of yellow leaf rate and fallen leaf rate with high accuracy.

TABLE I. Evaluation of image classification of square images

Class Name	Precision	Recall	F-Value
Green	0.892	0.928	0.909
Yellow	0.945	0.927	0.935
Others	0.921	0.928	0.924

Details of the precision rate are shown in Table II. The precision rate is an evaluation index that indicates how accurate the prediction was. Looking at Table II, we see that the proportion of images classified as green that were actually labeled as yellow was 0.082, and the proportion of images labeled as other was 0.027. In other words, there were more images erroneously predicted to be green that were labeled as yellow than as other. This suggests that while the system was relatively accurate in classifying images where the correct answer was other classes such as trunks and branches, it is possible that the classification of green and yellow classes did not capture the subtle changes that occur when leaves change from green to yellow. The classification accuracy is significantly better than the classification performed in the preliminary experiment using a specified HSV value range. In particular, there are almost no cases where leaves that should have been classified as green or yellow because they were shining in the light are misclassified as neither green nor yellow. However, with the specimen tree, after the day the leaves turned yellow, images were observed in which shadows were cast by the sunlight, and these parts were mistakenly classified as green. Therefore, it is necessary to aim to improve accuracy by devising photography methods and image processing methods that are not affected by the direction of the sun or shadows.

TABLE II. Details of Precision Rate

		Classification results		
		Green	Yellow	Others
Actual	Green	0.892	0.042	0.040
	Yellow	0.082	0.945	0.039
	Others	0.027	0.013	0.921

TABLE III. Objective and explanatory variables of the prediction model

Objective variables	Explanatory variables
Yellowing and fallen leaf rates three days later	Average yellowing rate for the past three days
	Average falling leaf rate for the past three days
	Illuminance
	Average of illuminance and CO_2 integrated value for three days
	Additional value of average illuminance from 6:00 to 18:00 on the same day

VII. Prediction Results and Discussion

Using the ResNeXt image classification model, we were able to classify images into three classes: green leaves, yellow leaves, and others, with an accuracy of over 90%. Using these results, it became possible to calculate the rate at which leaves turn yellow and fall to determine whether the best time to see the yellow leaves is. Tourists need more information than this. Not just whether the leaves are turning yellow now, but also predictions about when they will turn yellow and when they will fall. We will build a predictive model using changes in past image data and weather information from sensors.

The objective variables and explanatory variables used in the LightGBM analysis were defined as shown in Table III for the leaf yellowing rate prediction model and leaf fall rate prediction model. Note that temperature, humidity, and air pressure, which were planned to be used as explanatory variables, were not used as explanatory variables because only fixed values were recorded from the middle of the observation period. For the explanatory variables in Table III, the objective variables were predicted based on the average leaf yellowing rate over the past three days and the average leaf fall rate over the past three days. In addition, the objective variables were predicted based on the average illuminance and the integrated value of illuminance and CO_2 over three days, as sunlight and photosynthetic activity would affect the objective variables. Furthermore, the average illuminance value from 6:00 to 18:00 on the same day was added to replace the integrated temperature to improve the prediction accuracy. Regarding the objective variables, the prediction period for yellowing and leaf fall judgment in previous studies was three days later, so the objective variables in this study were set to the leaf yellowing rate and leaf fall rate three days later from the last day of the average value of the past three days. Note that these data are saved every minute. Therefore, for the data at 12:00 on November 10, 2024, the average value of the explanatory variables over the past three days is the average value of the data from 11:59 on November 8 to 11:59 on November 10, 2024, and the target variables are the yellowing and falling leaf rates at 12:00 on November 13, 2024.

Figures 4 and 5 show the measured and predicted values of the percentage of yellowing leaves defined by Eq. (1) and Eq. (3), respectively, and Figure 6 shows the measured and predicted values of the percentage of defoliation. Furthermore, Table IV shows the evaluation of the yellowing leaf rate prediction model and the defoliation rate prediction model.

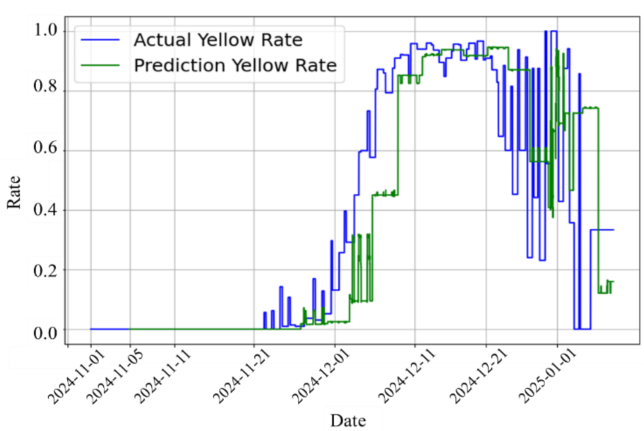

Figure 4. Actual value (blue) and predicted value (green) of the yellowing rate (Eq.(1)).

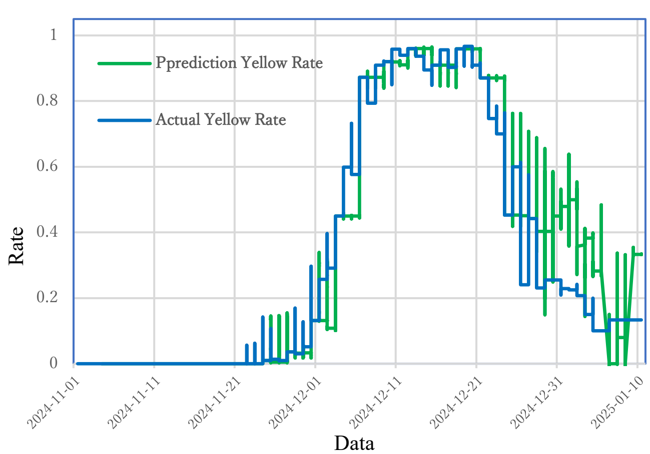

Figure 5. Actual value (blue) and predicted value (green) of the yellowing rate (Eq.(3)).

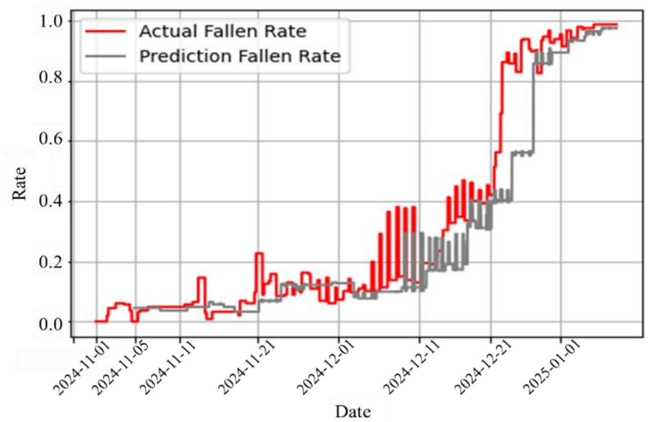

Figure 6. Actual value (red) and predicted value (gray) of leaf fall rate.

Figures 4, 5 and 6 show that the predicted values of the yellowing and falling leaf rates fluctuate about five days later than those calculated from the ginkgo image. In addition, after the fluctuation, there is no fluctuation and the rate remains flat for about three days. The reason for the approximately five-day delay in the fluctuation is thought to be that the data learned when the model output the predicted value of the evaluation data was from five days ago, so it was not possible to predict it as time-series data. In addition, the reason for the leveling off is that the yellowing and falling leaf rates were restricted to extract only the ginkgo image and only the time when the illuminance was within a certain range, leaving the yellowing and falling leaf rates blank for the time when the illuminance was outside the certain range. To fill this gap, the leaf yellowing rate and leaf fall rate from the most recent time when the illuminance was within a certain range were used. As a result, while the explanatory variables fluctuated during the learning data period, the objective variables, the leaf yellowing rate and leaf fall rate, did not fluctuate and remained flat during the period when the illuminance was outside of a certain range, so it is thought that the predicted values also produced similar outputs.

The data used in earlier published work contained approximately 10% overlapping timestamps. This is thought to be due to delays in data communication, so in this study, the duplicated data was removed.

TABLE IV. RMSE OF EACH REGRESSION MODEL

Model	RMSE
The yellowing leaf rate (Eq.(1)) prediction model	0.163
The yellowing leaf rate (Eq.(3)) prediction model	0.114
The defoliation rate prediction model.	0.083

Table IV shows that the RMSE (Root Mean Squared Error) of the leaf yellowing prediction model based on the percentage of yellowing leaves defined in Eq. (3) is 0.114. RMSE is an index that indicates the difference between the predicted value and the actual percentage of leaf yellowing or falling. This means that there is an average error of 0.114 between the predicted and actual values. This is a significant improvement over the RMSE of 0.163 for the leaf yellowing prediction model based on the percentage of yellowing leaves defined in Eq. (1). Comparing Figures 4 and 5, the difference becomes more pronounced as the percentage of falling rate increases, as shown in Figure 6. However, an RMSE of 0.114 means that even if the leaf yellowing rate is predicted to be 0.8, the actual result is 0.686 if it is low, or 0.914 if it is high, which is still not sufficient accuracy.

VIII. Conclusion and Future Work

In this study, we first proposed a method for quantifying the degree of leaf yellowing and defoliation in ginkgo trees using deep learning–based image classification. Although variations in observation dates and leaf density influence the apparent leaf color in ginkgo images, the developed high-accuracy classification model enabled reliable extraction of yellowing and falling rates.

We then evaluated a prediction method that estimates the yellowing and falling rates three days in advance, using processed meteorological data as explanatory variables.

Several challenges remain for observation methods utilizing IoT devices. First, the accuracy of image classification must be improved by developing imaging strategies that minimize the influence of sunlight direction and shadows. Additionally, it will be necessary to detect anomalies in meteorological measurements and to address sensor failures through sensor redundancy.

In this study, malfunctions occurred in the temperature, humidity, and atmospheric pressure sensors, rendering their measurements unusable. Incorporating these sensor values, in addition to illuminance and carbon dioxide concentration data, is expected to further improve prediction accuracy. In particular, atmospheric pressure is closely related to weather conditions and may complement illuminance measurements.

Future challenges also remain in the method for estimating yellowing and falling rates from ginkgo images. The dataset must be expanded by developing image processing techniques capable of accurately extracting color information from images that are excessively bright or dark. Moreover, because images were captured only between 6:00 and 18:00, a future task is to obtain continuous image data throughout the day without relying on costly equipment. Since the measurement site in this study was limited to a single location, it will also be necessary to verify the applicability of the proposed method to trees in different environments.

By addressing these issues, we aim to achieve fully automated prediction of yellowing and falling timing for individual specimen ginkgo trees.

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