RESEARCH ARTICLE https://doi.org/10.7235/HORT.20200061

Development of a Cut Rose Longevity Prediction Model Using Thermography and Machine Learning

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Abstract

To predict the longevity of cut roses (*Rosa hybrida* L.), we used thermal image analysis on '3D', 'Kensington Garden', and 'Hera' rose cultivars. At blooming stage, the temperatures of leaves and petals were similar to or slightly lower than the air temperature. When the temperature of leaves and petals increased by 2°C compared to the air temperature, no symptoms such as senescence were visible in the leaves and petals. However, three days after the temperature increase, significant visual senescence was observed and the temperature of leaves and petals decreased back to that of the air temperature. Based on this data, we identified three different stages of cut roses: (1) the blooming stage, (2) the last stage with no visual senescence, and (3) the stage with significant visual senescence. To embody a longevity prediction model for cut roses, the temperature difference between the leaf of 'Hera' and the air were chosen for the practice data for the model. After the machine learning process, a model with 100% accuracy was obtained. According to the model, when the temperature of a cut rose leaf is lower than the surrounding air, it is undergoing its blooming stage, while when it is higher it is undergoing the senescence stage. Using logistic regression with machine learning, a value of 1 indicates the senescence stage and a value of 0 indicates the blooming stage. This study suggests that current smart farming techniques used for cut roses are first-generation level, which means there are limitations in environmental control when using a remote control system and partially automatic system. To upgrade this process and overcome these limitations, an optimal model to predict the longevity of a cut rose is needed.

Additional key words: artificial neural network, cut flower, non-destructive testing, thermal image, vase life

Received: July 21, 2020
Revised: August 10, 2020
Accepted: August 20, 2020

HORTICULTURAL SCIENCE and TECHNOLOGY
38(5):675-685, 2020
URL: http://www.hst-j.org

pISSN : 1226-8763
eISSN : 2465-8588

This work was supported by a research grant (318063033HD030) from the Korea Institute of Planning and Evaluation for Technology in Food, Agriculture, and Forestry (IPET).

Introduction

Among ornamental plants, cut flowers comprise approximately 32.6% of the flower market in South Korea (MAFRA, 2018). For cut flowers, conserving freshness is more important than for any other flowering plant (An et al., 2018). Among these, roses (*Rosa hybrida* L.) are the most popular globally, with an annual market volume in Europe and USA of one trillion Won (Korean Won) (Roberts et al., 2003; Lee et al., 2018).

The quality of cut roses is influenced by the cultivar and growth environment before the harvest, and by the levels of ethylene and the presence of pathogens, such as bacteria, after harvest. Microorganisms found within the vascular tissues of the stem influence the longevity of roses after harvest (Hoogerwerf et al., 1989; Oh et al., 2017), as vascular blockages reduce water absorption, which leads to water stress and the bent-neck symptom, and in turn a degradation of the quality and ornamental value of cut roses (Burdett, 1970; van Doorn, 1989).

A method to predict and diagnose the quality of roses is needed to overcome the shortcomings of conventional destructive methods. Specifically, non-destructive testing (NDT) technology is needed to identify the status from the physiological, biochemical, and stress response quickly, effectively, and with minimal damage to the cut rose (Kim et al., 2018b). NDT can monitor and predict changes in a plant's physiological condition, enabling practitioners to reduce adverse symptoms during the early stages of stress (Chaerle and Van Der Straeten, 2000). One such NDT is thermal image analysis, which monitors plant growth, and enables prediction and diagnosis of water and pathogenic stress. Zia et al. (2011) monitored physiological responses to water stress in maize (*Zea mays*) using infrared thermography. The temperature difference between healthy cucumber (*Cucumis sativus*) leaves and leaves infected with downy mildew was visualized using infrared thermography before visible symptoms appeared (Lindenthal et al., 2005). Lee et al. (2017) also used thermal imaging to diagnose major fungal diseases before the appearance of visible symptoms in cucumber. Another study by Lee et al. (2019) showed that vase life of lily (*Lilium* sp.) could be predicted by differences between the air temperature and leaf/petal temperature of the cut lily after harvest.

Predictive models using machine learning algorithms require the collection and analysis of large volumes of data from IoT (internet of things). In agriculture, researchers use machine learning techniques such as prediction and classification. In 1980, researchers applied machine learning to determine if plants were under stress from disease. As a result, they obtained more accurate results than conventional assessments (McQueen et al., 1995; Lee and Choe, 2009), enabling agricultural professionals to apply this method to a variety of contexts globally to improve crop productivity and increase profits. Thus, this study aimed to generate a predictive model for the longevity of cut roses using thermal image analysis and machine learning.

Materials and Methods

Testing Materials

Three cut rose (*Rosa hybrida* L.) cultivars, '3D', 'Kensington Garden', and 'Hera', were grown in a greenhouse located in Gangjin, Jeollanam-do, Korea. Cut roses were harvested on a commercial stage (Kumar et al., 2008) and immediately immersed in tap water, then directly transported to the laboratory. Roses were cut 45 cm below the flower and leaves were removed from the lower 15 cm. Each cut stem was inserted into an Erlenmeyer flask containing 500 mL of distilled water.

Thermal Image Analysis

The temperature of each cut rose and the surrounding air was measured using an infrared thermal camera (FLIR 620, FLIR systems USA) with 640×480 pixels and a temperature span of -40 to 650°C (Fig. 1). Air temperature was recorded every 30 minutes by a data logger (WatchDog 1450, Spectrum Technologies Inc, USA), placed 1 m away from the cut rose.

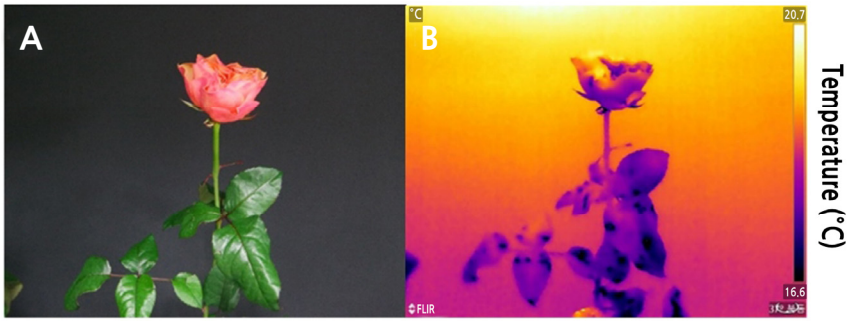

Fig. 1. An example of a digital image (A) and an infrared thermal image of a cut rose taken using a FLIR infrared camera (B). Color bar located on the right side of (B) indicates the temperature range.

Cut roses were tested under controlled conditions: temperature, relative humidity, and photoperiod were 17°C ± 4°C, 30% ± 5%, 12/12 hours, respectively. Thermal imaging was performed in the dark and krypton lamps (60W) were used for 10 minutes before the measurement to release heat energy from the plant. For each of the three rose cultivars, thermal imaging photographs were taken from four plants per cultivar under the same environmental conditions. These were photographed every 24 h until the end of the longevity of cut roses. A temperature average spot was selected for petals and leaves. Images taken by the thermal imaging camera were analyzed using FLIR Tools+ program (FLIR Systems Inc., USA). To confirm temperature changes of cut roses, the images were taken by a digital camera and visible changes were recorded by an observer.

Cut Flower Quality

A separate set of cut roses was prepared similarly to those used in the thermal image analysis with twelve replications. In this sample, we observed changes in the fresh weight, water uptake, water balance, and stomatal size every other day. The fresh weight was measured on the first day, then subsequent measurement were compared to the original. Water uptake was calculated by subtracting the weight (flask + distilled water) from that of the previous day and the water balance was obtained by subtracting the amount of transpiration from the water uptake. A hole (1 cm diameter) in the center of the flask was covered with aluminum foil to prevent natural evaporation. An optical microscope (CX 31, Olympus, Japan) at 400× magnification was used for observations under dark and light conditions so that plants were subjected to an uninterrupted 12/12 h cycle. Stomatal imaging was conducted using a microscope camera (T500, eXcope, China) and the stomatal size was analyzed using software eXcope Lite (eXcope, China). The rate of change in the stomatal size was calculated as, the change of stomatal area between the light and dark condition [rate of change = stomatal area (light) / stomatal area (dark) ×100%].

Statistical Analysis

One-way analysis of variance was conducted using SPSS 25.0 (IBM Inc., USA). The thermal imaging temperature comparisons over time were done using Duncan's multiple range test, with a significance level of $p \leq 0.05$.

Model Analysis Using Machine Learning

Supervised machine learning was used to train a model to estimate the longevity of cut roses using the difference between the temperature of rose leaves and that of the surrounding air. To predict the longevity of cut roses, using a logistic regression, one of the following classifications was applied. A sigmoid function (whose value is between 0 and 1) was used: $g(z) = \frac{1}{1+e^{-z}}$. Therefore, the modeling hypothesis was as follows: $H(X) = \frac{1}{1+e^{-(WX+b)}}$, where H is the predicted values, W is the weight and b is the bias. The computer aims to find the optimal W and b using a cost function, expressed as follows:

$$Cost(W,b) = \frac{1}{m}\sum c(H(x),y) \tag{1}$$

where, m = number of data points

$c(\ )$ = cost function

y = observed values

$$c(H(x),y) = \begin{cases} -\log(H(x)) & : y=1 \\ -\log\ (1-H(x)) & : y=0 \end{cases} \tag{2}$$

$$c(H(x),y) = -y\log\ (H(x)) - (1-y)\log\ (1-H(x)) \tag{3}$$

$$\therefore\ Cost(W,b) = -\frac{1}{m}\sum y\log\ (H(x)) + (1-y)\log\ (1-H(x)) \tag{4}$$

Results

Predicting Cut Rose Longevity Using Infrared Imaging

Three cultivars of cut roses were used in the study because of their differences in appearance, flowering, and aging conditions. The thermal imaging results for each cultivar are shown in Fig. 2. The ‘3D’ cultivar was in full bloom on the 4th day and the temperature difference between the surrounding air and the petals and leaves was 0.2 and 0.1°C, respectively (Fig. 3). The ‘Kensington Garden’ cultivar showed a slight temperature difference, with that of the petals and the leaves being 0.6°C and 0.4°C higher than the surrounding air, respectively. However, on the 8th day, the petals and leaves from the ‘3D’ and ‘Kensington Garden’ cultivars were, on average, 2°C higher than the surrounding air. At this stage, no visual senescence was observed, but three days after this temperature rise, we observed visible senescence.

By contrast, the ‘Hera’ cultivar was in full bloom on the 3rd day, with a temperature difference between the surrounding air and the petals and leaves being 0.7 and 1.6°C, respectively, which was higher than the other two cultivars. On the 6th day, petals and leaves were 2.4 and 1.3°C higher than the surrounding air, respectively. On the 8th day, we observed significant visual senescence, but no significant temperature difference between the surrounding air and the leaves and

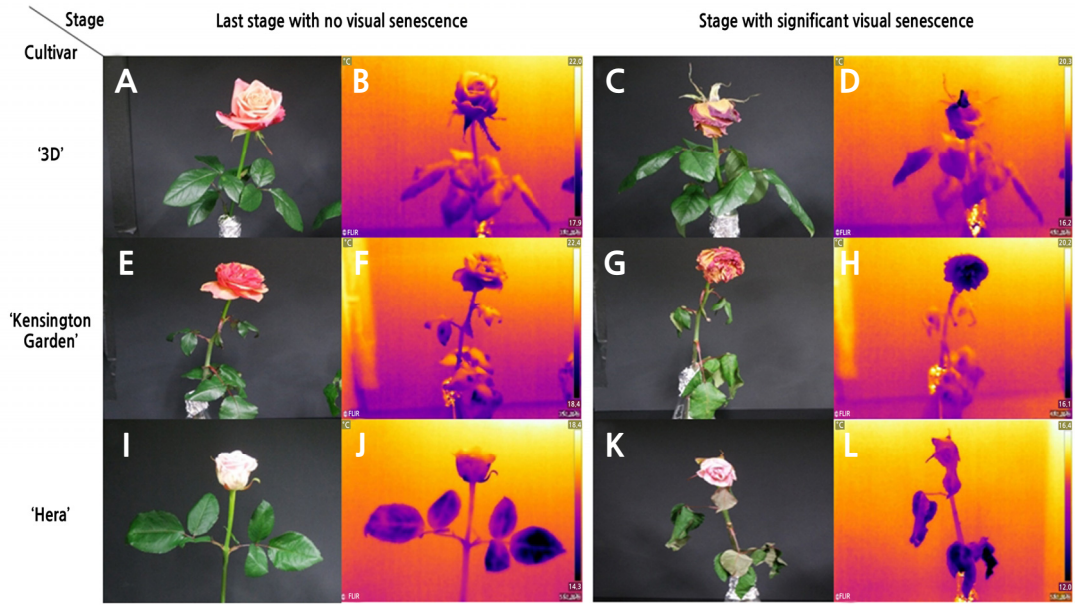

Fig. 2. Digital (A, C, E, G, I, K) and thermal images (B, D, F, H, J, L) of the cut rose cultivars '3D' (A-D), 'Kensington Garden' (E-H), and 'Hera' (I-L) on the day of the last stage with no visual senescence and the day of significant visual senescence.

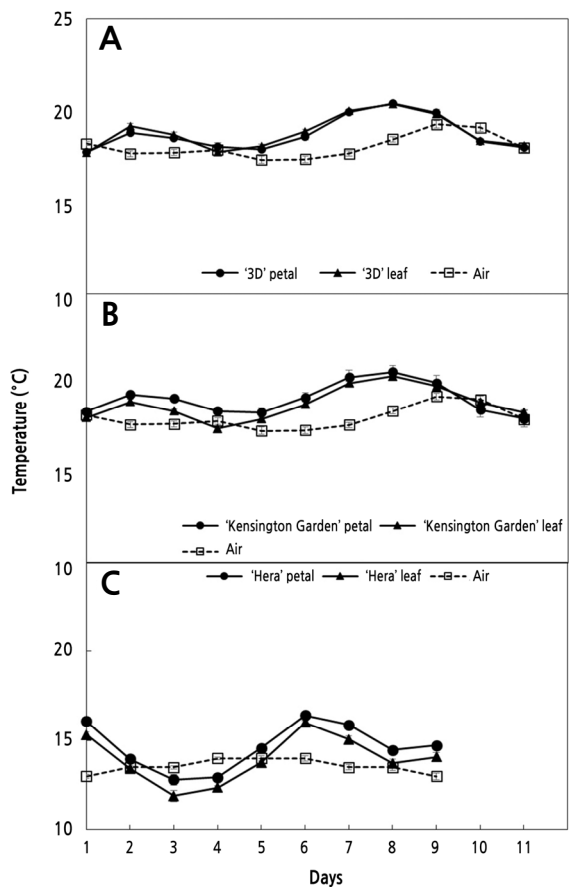

Fig. 3. Differences between air and petal/leaf of temperatures of cut rose cultivars '3D' (A), 'Kensington Garden' (B), and 'Hera' (C) through thermal image analysis. Vertical bars indicate the standard error (n = 8).

petals. When the other two cultivars showed the same temperature pattern, they also had significant visual senescence. After analyzing data from all three cultivars for the temperature differences between the air and the leaves and petals (Table 1), significant temperature differences were recorded between distinct stages, which are: (1) the blooming stage, (2) the last stage with no visual senescence, and (3) the stage with significant visual senescence.

Table 1. Difference between air and petal/leaf surface temperatures of cut rose cultivars '3D', 'Kensington Garden', and 'Hera' at three different stages

Stage	Difference of temperature	
	Petal	Leaf
Blooming	0.16 ± 0.05[z] c[y]	− 0.59 ± 0.17 c
Last stage with no visual senescence	2.49 ± 0.72 a	2.32 ± 0.67 a
Stage with significant visual senescence	0.77 ± 0.22 b	0.73 ± 0.21 b

[z]Mean ± SE

[y]Mean separation within columns by Duncan's multiple range test, $p \leq 0.05$ (n = 12).

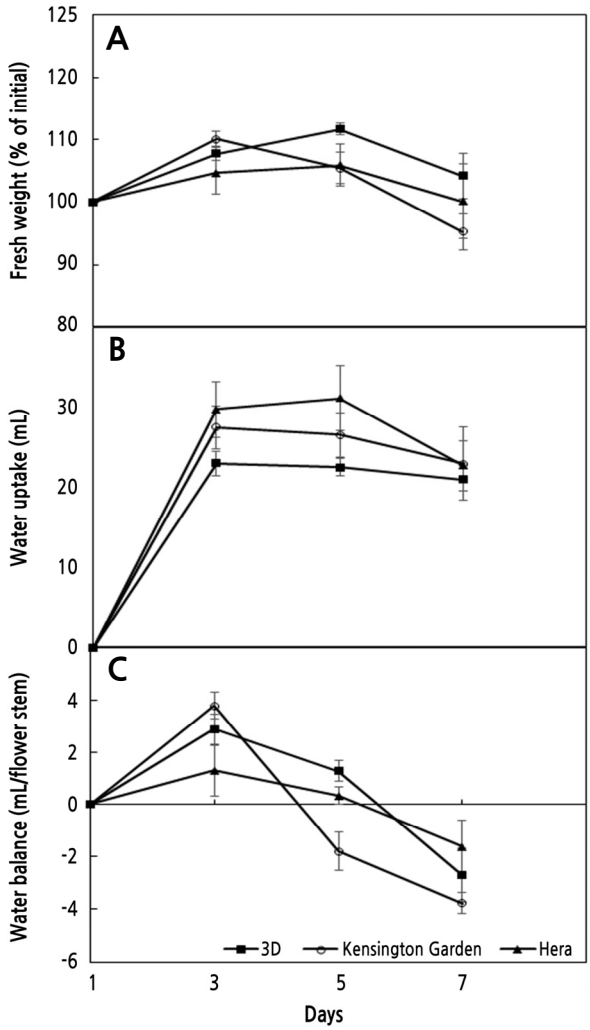

Fig. 4. Change of fresh weight (A), water uptake (B), and the water balance (C) of cut rose cultivars '3D', 'Kensington Garden', and 'Hera'. Vertical bars represent standard errors of the means (n = 5).

After analyzing the fresh weight, water uptake, and water balance (Fig. 4), all three cultivars seemed to start experiencing water stress on the 5th day, two of which ('3D' and 'Hera') showed a slight rise in the temperature of petals and leaves. The 'Kensington Garden' cultivar has a characteristic of longevity ending before fully blooming due to a lack of water. From this characteristic, 'Kensington Garden' roses show a stronger sensitivity to water stress than the other cultivars considered in this study. Based on this result, it could be found that predicting the longevity of cut roses is more effective using cultivars sensitive to water stress.

The analysis of the stomatal size change rate was intended to determine the relationship between the stomatal size and leaf temperature, which has a strong association. Fig. 5 shows the stomatal size change rate of each cultivar on the first day and senescence day of the experiment. On the 1st day after the harvest, the stomatal size change rate was 31.2% for 'Kensington Garden' and 0.6% for 'Hera'. The stomata were opened in the light and closed in the dark, hence the stomatal size change rate was large. However, on the 7th day (when a significant temperature change was recorded), the stomatal opening and closing were not working properly and decreased by 50.6% (−19.4%) in 'Kensington Garden' and by 12.6% (−12.0%) in 'Hera;' those were not significant changes, possibly because stomata were already closed due to water stress. For the '3D' cultivar, the stomatal size change rate was large on the 1st day (72.2%) and the 7th day (64.7%).

Longevity Model

Python/TensorFlow frameworks were used to perform machine learning using the following model as training data, using recorded temperature from the leaves of the 'Hera' cultivar and the surrounding air. To minimize the cost function, the gradient descent algorithm was used to obtain optimal W (weight) and b (bias), as shown below:

$$W = \begin{bmatrix} -0.8216 \\ 4.7028 \end{bmatrix}, b = [0.4621] \tag{5}$$

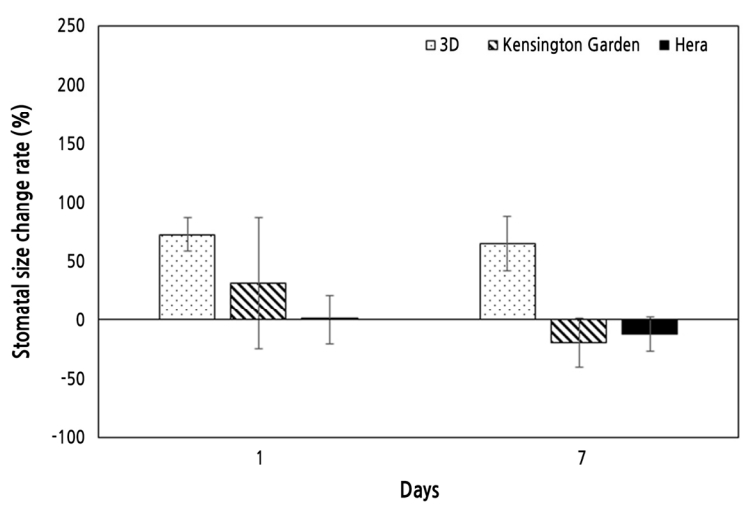

Fig. 5. Stomatal size change rate [= stomatal area (light) / stomatal area (dark) ×100%] on each day for cut rose cultivars '3D', 'Kensington Garden', and 'Hera'. Day 1 = day of first test, Day 7 = starting day of senescence. Vertical bars represent standard errors of the means (n = 4).

Even though there was a small amount of training data with replications of 120, the machine learning algorithm trained a model with 100% accuracy, which was confirmed after running the data through with it 10,000 iterations.

After analyzing the trained model by inputting the data, we found that the blooming stage corresponded to a decrease in the plant's temperature compared to the surrounding air, while the senescence stage corresponded to an increase in the plant's temperature compared to the surrounding air (Fig. 6). Extra 'Kensington Garden' data was added to increase the robustness of the trained model.

Using the binary logistic regression in machine learning, the states of cut roses were found, in which a value of 1 indicates the senescence stage and a value of 0 indicates the blooming stage (Fig. 7). By distinguishing the stages of senescence and blooming before changes became visible, a model for predicting the longevity of cut roses was trained. However, the '3D' cultivar was in full bloom even though it was experiencing the senescence stage, as on day 11 (i.e., the day the senescence stage started), the temperature difference measured was the same as on the day of the blooming stage. This research demonstrated the possibility of predicting the longevity of cut roses using thermal image analysis and machine learning. In future studies, we plan to add more data to develop a more robust model.

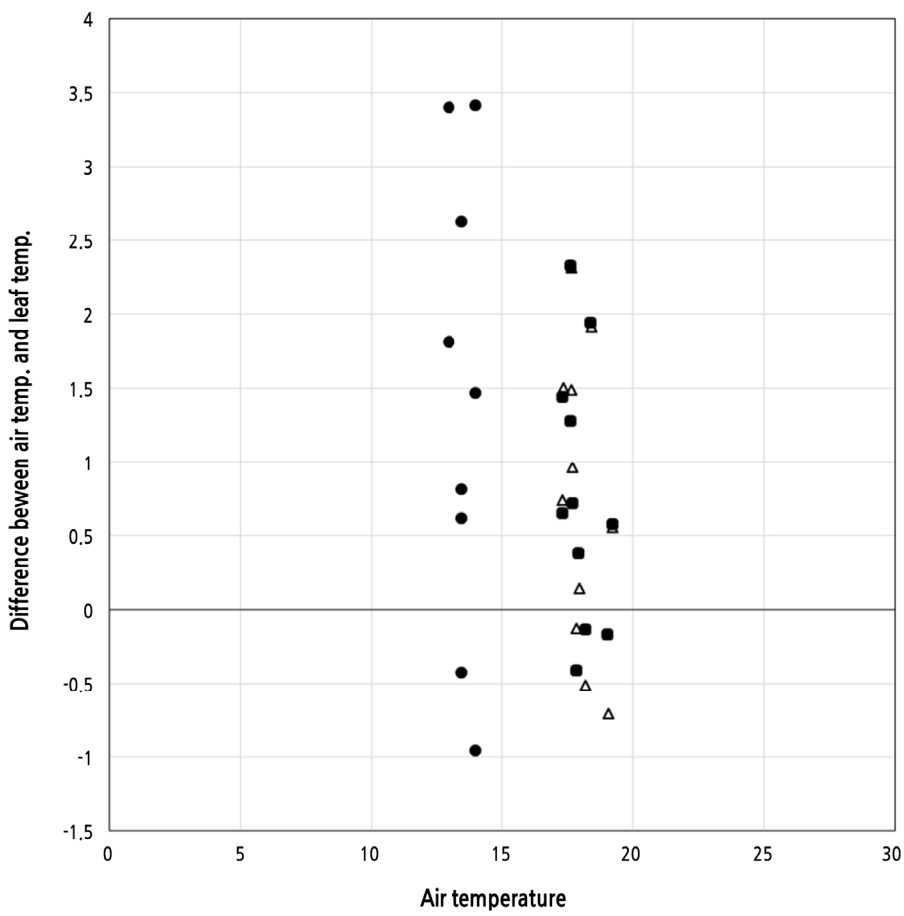

Fig. 6. Senescence and blooming status of rose cultivars '3D' and 'Kensington Garden' using the trained model of the 'Hera' dataset. [value = leaf temperature - air temperature (+ : senescence, - : blooming)] (●: Extra 'Kensington Garden', ■ : 'Kensington Garden', △: '3D').

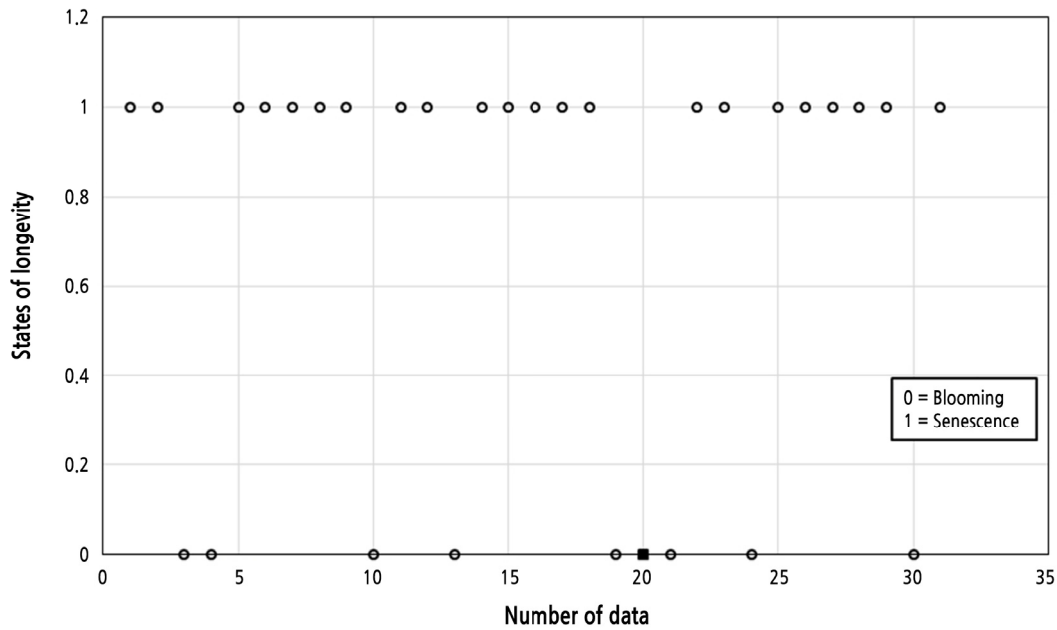

Fig. 7. States of longevity (value 0: blooming, value 1: senescence) result from machine learning using logistic regression (○: '3D' and 'Kensington Garden', ■: error point).

Discussion

Stomatal control is a key determinant of photosynthesis and water physiology affecting plant growth and longevity, and stomatal conductance for transpiration is an important physiological variable to be monitored. It is possible to estimate the transpiration rate with thermal imaging because transpiration influences the leaf energy balance and leaf temperature (Costa et al., 2013).

Therefore, to predict the longevity of cut roses, we analyzed thermal images of three rose cultivars. In all three cultivars, the blooming stage was characterized by the leaves and petals temperatures showing very small difference compared to the surrounding air, while the onset of senescence was characterized by a 2°C increase in the temperature of petals and leaves compared to the surrounding air, although no visible changes were observed in the morphology of the cut roses. Three days after senescence became visually apparent, the temperature of leaves and petals were again similar to that of the surrounding air. According to Idso (1982), when transpiration is inhibited due to water supply or disease, leaf temperature is higher than that of the air, hence temperature changes in the leaves might indicate the onset of morphological symptoms. Lee et al. (2019) analyzed the longevity of cut lilies using thermal images, and found that differences between the leaf temperature and that of surrounding air was 3°C before the onset of senescence. Another study using thermal imaging showed that cucumber water stress could be predicted by an increase in leaf temperature, as this often occurred before wilting could be observed (Lee et al., 2014). Similarly to our findings, Hashimoto et al. (1984) reported that when sunflower (*Helianthus* spp.) leaves were subjected to water stress, the stomata closed and leaf temperature increased. When reaching the end of their vase life, roses are under stress due to lack of water and nutrients, and the temperature of the cut flowers was lower than the surrounding air temperature (Kim et al., 1999). Another study

showed the same result (Kim et al., 1999) that the death of leaf cell resulted in uncontrolled water loss and a temperature decrease (Wang et al., 2012).

In et al. (2016) showed that there was a high correlation between the transpiration rate and the temperature change of the leaves of cut roses. This allowed them to develop a model to predict the longevity. After examining the water balance and changes in the stomatal size of '3D', 'Kensington Garden', and 'Hera' cut roses, our findings show that the water balance became negative and the temperature of the leaves and petals increased, on the same day. Additionally, on the day when the temperature change of petals and leaves occurred, we also recorded a reduction in the stomatal size, suggesting that the opening/closing of stomata was not functioning properly. The plant's leaf temperature is increased due to water stress and because the stomata are closed (Jones and Leinonen, 2003). Our findings are consistent with previous studies that showed that leaf temperature can be successfully estimated using thermal imaging before any sign of disease or stress becomes visible (Chaerle et al., 2004).

To implement a longevity prediction model of cut roses, machine learning was performed by selecting the difference between leaf temperature and air temperature of the 'Hera' cultivar as training data for the model. The resulting model had 100% accuracy. Our model suggested that the blooming stage occurs when the leaf temperature is lower than the air temperature and the last stage with no visual senescence occurs when the temperature is high. Using logistic regression of machine learning, a value of 1 indicates the senescence stage and a value of 0 indicates the blooming stage. The trained model was developed using small amount of data, which gave a result with 100% accuracy. But, large amount of test data ('3D' and 'Kensington Garden') was used in the trained model which gave an error. The error in the '3D' cultivar occurred due to the small dataset, which could be solved by using a larger amount of data in the future. Kim et al. (2018a) used machine learning to determine the ripeness of strawberries by using their color. Their model had 96.1% accuracy, according to a linear discriminant analysis. Another study used machine learning to predict changes in the price of cabbage depending on the influence of climate factors (Oh et al., 2019), and Korea Telecom Corporation (KT Corp.), a domestic company leading smart farm commercialization, introduced big data and machine learning technology to provide the optimal cultivation method by collecting cultivation data (Kim and Cho, 2017). Na (2018) also developed a model which can classify the behavior of a black goat, using a support vector machine algorithm and reinforcement machine learning technique, which confirmed that the behavior analysis accuracy increased to 88%. Therefore, it is valuable to generate an optimal model that can predict the longevity of cut flowers.

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