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Quality Estimation of Net Packaged Onions during Storage Periods using Machine Learning Techniques

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Abstract Onions are a significant crop in Korea, and cultivation is increasing every year along with high demand. Onions are planted in the fall and mainly harvested in June, the rainy season, therefore, physiological changes in onion bulbs during long-term storage might have happened. Onions are stored in cold room and at adequate relative humidity to avoid quality loss. In this study, bio-yield stress and weight loss were measured as the quality parameters of net packaged onions during 10 weeks of storage, and the storage environmental conditions are monitored using sensor networks systems. Quality estimation of net packaged onion during storage was performed using the storage environmental condition data through machine learning approaches. Among the suggested estimation models, support vector regression method showed the best accuracy for the quality estimation of net packaged onions.

Keywords Net packaged onion, Wireless sensor network, Machine learning technique

1. Introduction

Onion (*Allium cepa L.*) is known as a vital crop around the world because it has a variety of healthy ingredients like fiber, vitamins, organic acids, phenolic compounds, and other antioxidants[1]. Especially in Korea, it was reported that the cultivation of onion has increased by 4% for last several years[2]. Onions are generally planted in the fall and harvested from April to June of the next year, and then long-term storage is required to satisfy year-round supply. During long-term (almost one year) storage, onions are stored in cold room which controlled near 0°C, along with well-ventilated storage for longer shelf life. In Korea, onions are distributed mainly in the form of net packaging state after harvest. Onions in net packaging state help the onions breathe more than other closed-package systems. Also, the net packaging is made of tough material, so it is easy for workers to carry it. However, such a net packaging-based transport system may cause damage to onions. In addition, when rotten onions are found in the process, it is difficult to separate and remove them. However, harvesting happens primarily during the rainy season, a high moisture content of onions can cause its quality deterioration during long-term storage[3,4]. Moreover, physiological changes in onion bulbs during long-term storage can be affected by increased respiration, ethylene production, and other chemical compounds produce during the storage. In this way, it is important to consider breathing and physical properties in the post-harvest process of onions.

It was widely known that well-conditioned storage plays a main role in delaying the deterioration of the onions, and maintaining the optimum range of environmental conditions could prolong the onion's shelf life. There were several studies which have estimated onion quality and determined the optimal temperature during storage and distribution processes. To preserve the onion's quality, onions were kept at a low temperature of 0°C and humidity around 60-75%[5–7]. Like this, temperature and humidity are important environmental factors in storage that would affect the freshness of onions. The quality of fruits and vegetables comprises multiple characteristics: sensory, nutritional, and mechanical properties[8]. Among those qualities of crops, mechanical property means how a crop behaves in response to an applied force. Several studies for the mechanical properties of potatoes, cucumbers, and apples during transportation and storage have performed[9–11], and it was found that the external and internal forces can

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significantly influence mechanical damage in agricultural products. External forces are subjected to static and dynamic loads, resulting in injury, whereas internal forces can be caused by physical, chemical, and biological changes[12]. The quality parameters of an onion, such as bio-yield stress[13,14] and weight loss [15,16] were also studied to evaluate the quality change of onion for different storage conditions.

Recently, the field of quality control in agricultural products has employed advanced sensor network techniques such as innovative RFID, intelligent indicator packaging[17–20],and wireless sensor network (WSN) is also used to measure the quality of the agricultural products in distribution or storage process. Some studies have suggested that there was high relationship between the quality of crops and the environment data (temperature, humidity, and CO_2) of farmhouses that grow them[21,22]. Generally, industrial supply chain monitors and controls the storage and distribution stages using a wireless sensor network in order to control the quality of distributed products [18,23],however, there are few studies evaluating onion quality based on real-time environmental data.

Since decades ago, many statistical or artificial learning-based methods have been used to evaluate or predict crop quality. Among these techniques, modeling techniques based on artificial neural networks have recently been widely applied[24–27]. The machine learning algorithm is a type of method that uses historical data as input to predict new output values and becomes more accurate at predicting outcomes, in addition, supervised machine learning is implemented to these algorithms. Among the studies on onion quality prediction based on artificial neural networks, many of them used a kinetic model to predict the quality change in onions[28–31]. However, these models have structural limitations in reflecting dynamic data such as environmental information. Hence, in this study, we used a machine learning based approaches to develop quality estimation of onions during storage using environmental information. Especially, we employed a support vector regression method to estimate the quality of onions during storage since the method is known as one of effective solutions for the problem of small sample size and nonlinear attributes, which are exactly the quality attributes of onion during long-term storage.

In this study, we measured the environmental temperature and humidity of the storage condition, and observed the quality change (bio-yield strength, weight loss, and respiration rate) of the onions. Using these measurements, we developed and compared some quality estimation models using machine learning techniques such as multiple linear regression, partial least square regression, and support vector regression methods.

Material and Method

1. Sample and Equipment

As an experimental target, onions of the ‘Marusino 310’ variety harvested in March 2022 in Jeollanam-do, Republic of Korea were used. 'Marusino 310' is an extremely early growing onion variety, which is sown in early September and harvested in early March in Jeju Island or southern Jeollanam-do in a warm climate. The onion samples were transferred to cold-storage chamber right after harvesting without a curing process and stored in range of 0-5°C for 3 months from March to June. To monitor changes in the storage environment and the physical properties of onions in real time, a data acquisition device (Raspberry Pi 4B, Raspberry Pi Foundation, United Kingdom) and all-in-one sensor (SH-VT-260-010, Sohatech, Republic of Korea) including temperature, relative humidity, CO_2 sensing component and weight scale (ES-30ki, A&D Korea Ltd, South Korea) were used. A schematic of the monitoring systems is shown in Fig 1.

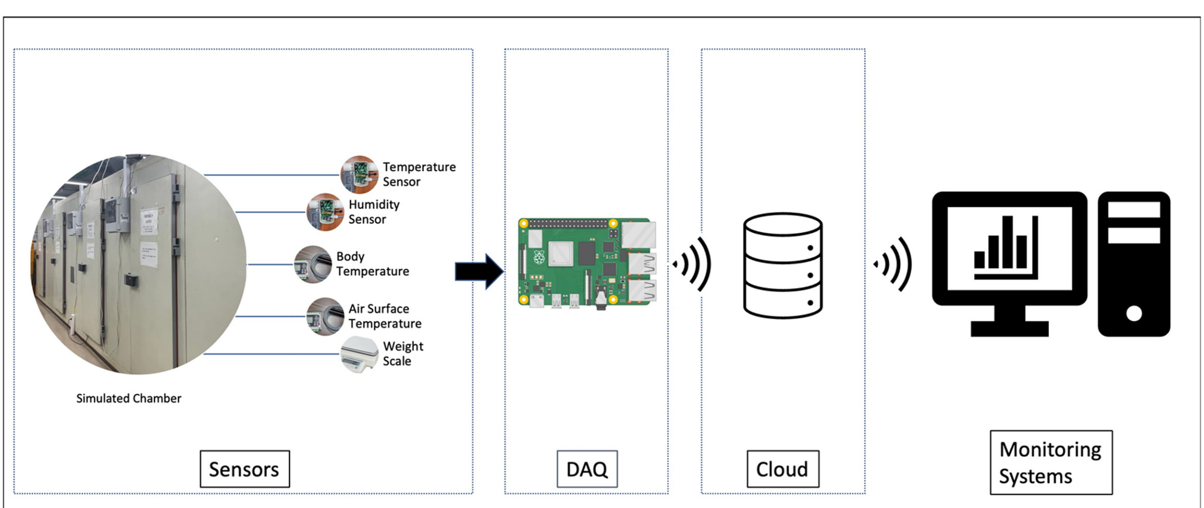

Fig. 1. Schematic of monitoring systems.

2. Quality Attributes measurement

To measure the deterioration of onion quality along with the storage time, several destructive experiments were conducted on a weekly basis. Twenty-five onions were randomly sampled in each experiment, twenty of which were used for physical property analysis and the other five for respiration rate analysis. Physical property analysis was performed through a penetration test using a 5 kN capacity Universal Testing Machine (Autograph AGS-X series, Shimadzu Corp, Japan). Before the penetration test, all onions were peeled, and cut in half parallel to the face penetrating the roots and stems. Then, the onion was placed in the machine above a flat plate, ensuring that the center of the probe was in alignment with the sample. Based on the standard for penetration test of food material of convex shape, 8 mm diameter probe at a speed rate of 25 mm/min was used[32]. Using the penetration results, bio-yield point was obtained as shown in the Fig. 2 and bio-yield stress was calculated based on it. The peeled onion samples and Universal Testing Machine used in the experiment are shown in Fig. 3 and Fig. 4.

The respiration rate was calculated by measuring the amount of CO_2 emitted by onion samples at room temperature for 4 h. To accurately detect the amount of CO_2, each sample was stored in a sealed 1 L jar, and 10 ml gas sample was taken with a needle and injected into the gas Chromatography (6500GC, YL Instrument, Korea) in every 2 h. This instrument uses argon as a carrier gas at a flow rate of 18 ml/min and 50°C as a column temperature. The respiration of onion is expressed in Eq. 1.

$$RCO_2 = \frac{Vf \times yCO_2}{t \times M} \tag{1}$$

where, RCO_2(ml/kg/h) is the respiration rate, Vf (ml) is the free mass of the jar, yCO_2 (decimal) is the volumetric concentration of CO_2, t is the time that the sample stored in the room temperature, and M is the mass of the product (kg).

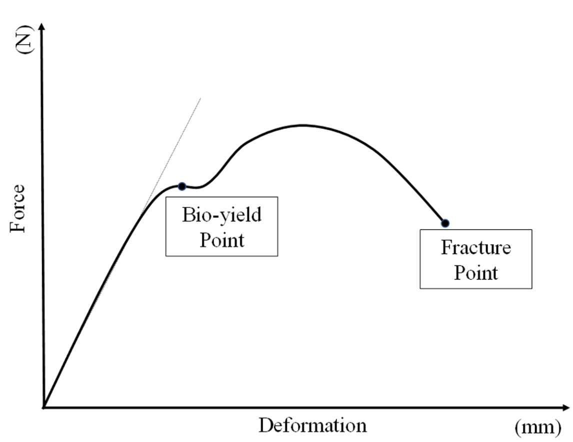

Fig. 2. General Force-deformation graph of penetration test.

Fig. 3. Peeled onion samples used in the experiment.

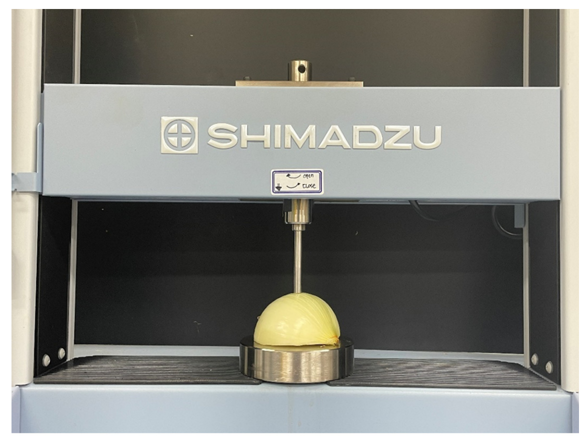

Fig. 4. Universal testing machine and 8 mm diameter probe used in the penetration test.

Weight change is another major factor in determining the quality of onions. In order to quantitatively represent the weight difference, the Weight Loss Rate was calculated based on the value obtained from the scale installed in the cold-storage chamber. The equation used in the calculation is shown in Eq. 2 below

$$\text{Weight Loss Rate(g/kg)} = \frac{(W_{(i+1)} - W_i)}{W_0} \tag{2}$$

where, W_0 is the initial weight and W_i is a weight in i_{th} day.

It is known that most weight changes during storage occur from water loss, which can be inferred through the transpiration rate. To compare with the measured weight change, the theoretical transpiration rate was calculated as shown in Eq. 3.

$$m = k_t(P_{SS} - P_\infty) \tag{3}$$

where, m represents a transpiration rate (g/kg·s), k_t is the transpiration coefficient (g/kg·s·Pa), P_{SS} is water vapor pressure at the evaporating surface of product (Pa), P_∞ is ambient water vapor pressure (Pa). As a theoretical reference, 850×10^{-9} g/kg·s·Pa was used as the transpiration coefficient value for onions[33,34].

3. Prediction Model

Models were developed to predict the bio-yield strength of onions by matching the data obtained from the storage experiment with three machine learning methods. The regression models used in this study were multiple linear regression (MLR), partial least squares regression (PLSR), and support vector regression (SVR). The temperature, relative humidity, and storage time data obtained throughout the storage period were used for the machine learning. In order to develop predictive models, the entire set of data was divided into 8:2 to construct training and test sets. Models were trained using train dataset, and parameters of models were optimized with 10-fold cross-validation on the train dataset. Performances of trained models were evaluated using the test dataset (Fig. 5). The regression models were evaluated by coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE), as shown in Eq.4-6, respectively. The regression analysis was performed in Python (Version 3.9.9).

$$R^2 = 1 - \frac{\sum (y_{act} - y_{pred})^2}{\sum (y_{act} - \bar{y}_{act})^2} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum (y_{act} - y_{pred})^2}{n}} \tag{5}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{(y_{act} - y_{pred})}{y_{act}} \right| \times 100 \tag{6}$$

An MLR model was developed to predict the bio-yield strength (y) of onions from a linear combination of time (t), temperature (T), and relative humidity (RH) data, as described in Eq. 7 with coefficients β_0, β_1, β_2, β_3 and standard estimation error ε.

$$y = \beta_0 + \beta_1 t + \beta_2 T + \beta_3 RH + \varepsilon \tag{7}$$

PLSR was another model used in this study for the prediction modeling based on the same dataset as in the MLR model. For the PLSR model, the number of latent variables was determined to perform the decomposition of the input variables (time, temperature, and relative humidity) and the output variable (bio-yield strength). The decomposition of the variables was performed in a way that the covariance between the input variables (X) and the output variable (Y) becomes its largest using the score matrix T and loading matrices P, and Q (Eq. 8). E and F are the residual matrices of the PLSR model.

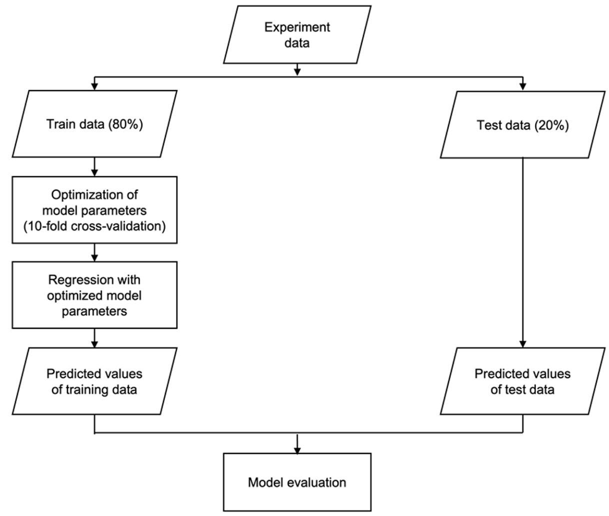

Fig. 5. Flowchart of model training and evaluation.

$$X = TP^T + E \tag{8}$$

$$Y = TQ^T + F$$

Lastly, SVR was used to develop linear and non-linear regression models from the dataset. In this study, three kinds of kernels were used including linear, polynomial, and radial basis function (RBF). Optimization of the parameters required for each kernel was performed through cross-validation. For the polynomial kernel, degree of the kernel was determined. For the RBF kernel, regularization parameter (C), kernel coefficient gamma (γ) and epsilon (ε) were determined.

Result and Discussion

1. Onion Quality Analysis

The most important thing in storing onions is the storage environment. The temperature and humidity affect the physicochemical properties of the onion bulb, which is essential to the degradation of the quality of the stored onions. As shown in Fig. 6(a), during the 10-week experiment period, the onions were stored at a temperature of 0~1°C. It was observed that the surface air temperature obtained with a temperature sensor between the onions was higher than the body temperature that probed the sensor inside the onions. The porosity of the reservoir allows gas exchange and heat transfer to occur between the storage temperature and the

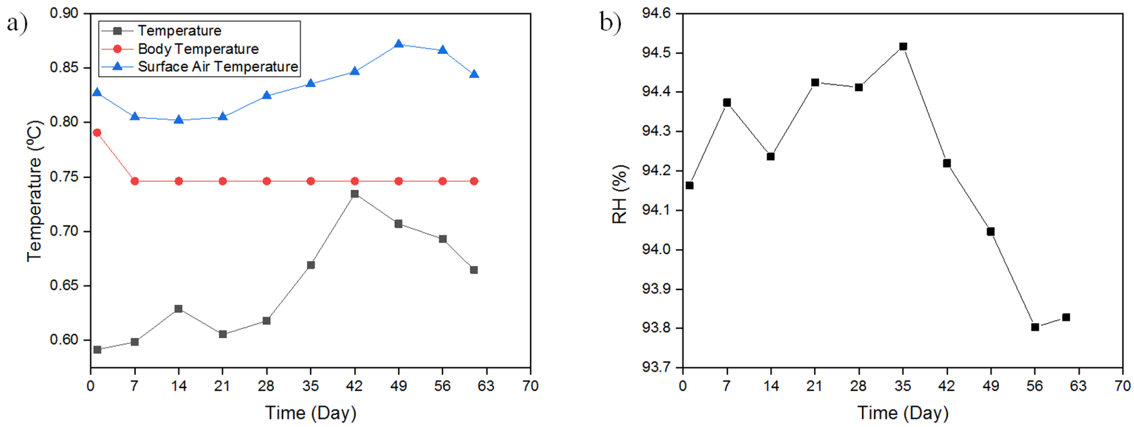

Fig. 6. Storage condition data. a) Temperature data during 10-week storage. b) Relative humidity during 10- week storage.

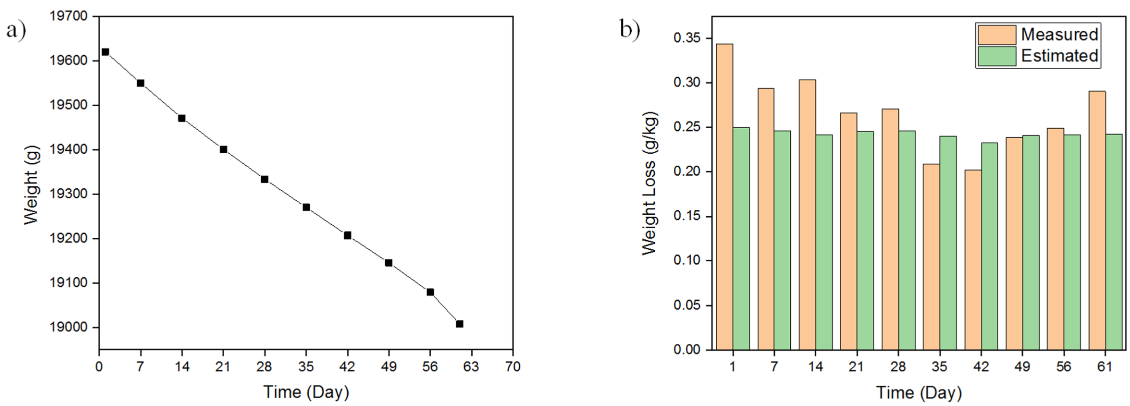

Fig. 7. Changes in weight of onion. a) The onion weight during storage. b) Weight Loss Rate of onion.

temperature of the onion bulb. The humidity was not controlled, but as shown in Fig. 6(b), it remained above 90% throughout the experiment.

As shown in Fig. 7(a), the weight of onions decreased by about 600 g during the experiment period and dividing it by the total onion weight corresponds to 3.06 g/kg. Since it occurred for 10 weeks, the weight loss of about 0.306 g/kg occurred every week. Fig. 7(b) shows how much weight loss occurred for each week. And when compared to estimated weight loss, which is theoretically calculated from Eq. 3, the estimated values are calculated based on the temperature and humidity. The contrast between the measured and estimated values is lightly discorded. Hypothetically, the reduced weight might be influenced by temperature and humidity. Therefore, the weight loss can be a key parameter for evaluating the freshness and quality of objects.

Fig. 8 shows the respiration rate of onions. Since onions are non-climacteric type, the respiration rate does not increase rapidly during the aging process. Therefore, it is presumed that the temporary increase in respiration rate between the 4th and 7th weeks of the experiment was due to the growth of spoilage microorganisms rather than an onion-specific problem.

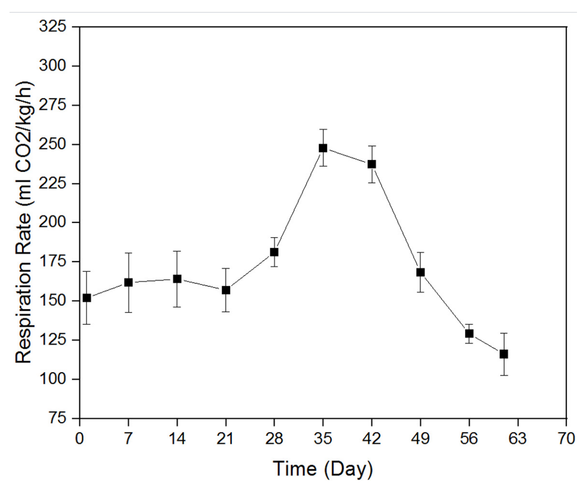

Fig. 8. Respiration rate of the onion during storage weeks. The data are expressed as mean ± SD of 5 samples. Vertical bars represent the standard errors of the means.

In this experiment, since onions were left in a box without being packaged in any packaging material, contamination could occur even in the case of a chamber environment. The

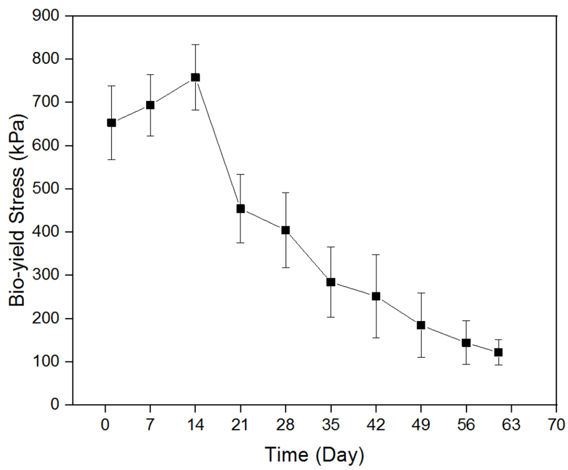

Fig. 9. Bio-yield stress in the onion during storage days. The data are expressed as mean ± SD of 20 samples. Vertical bars represent the standard errors of the means.

decreasing respiration rate is caused by the consequence of the physiological change in the onion, and the decrease leads to progressive death cell and onion decay.

Fig. 9 shows the bio-yield stress values measured on a weekly experiment. Bio-yield stress is stress in the bio-yield point where the bio-yield point is related to failure in the microstructure of the material associated with an initial cellular structure. The reduction in bio-yield stress is an important indicator of the chemical change in the onion being stored. The bio-yield stress of onion slightly increased at the beginning of the experiment and then decreased over time, presumably because the active transpiration influenced the loss of water and a low-temperature treatment, and as a result, it caused shrinking due to dehydration and softening due to chilling injury. Therefore, if the experiment had been continued after 10 weeks, the bio-yield stress value would have continued to decrease. The increase in stress for the first two weeks is judged to have a cold shock by putting the onion in a 0°C environment where it reaches a freezing point. Since curing was not performed before the experiment, the moisture content of onions may have been slightly higher than the average of the subjects, which may have an unsuitable effect on long-term storage.

2. Prediction Model

In this study, we measured respiration rate, weight loss, and bio-yield strength of onion samples. However, in the case of respiration rate, it was impossible to develop a meaningful machine learning-based time series prediction model due to its nonlinearity. In addition, in weight loss, it showed a trend of decreasing linearly with storage time, so there was no need to create a machine learning-based prediction model under the current experimental conditions. Considering these results, prediction modeling was performed only for bio-yield stress.

Table 1 presents evaluation metrics of regression models on train and test set. In PLSR, the highest performance was shown in cross-validation process when two latent variables were used. In SVR, model with RBF kernel showed the highest performance, and *C*, g, and ε were optimized to 0.0001, 10000, and 0.00001, respectively. R^2 of the models showed values of >0.8 for MLR and SVR, and 0.7773 for

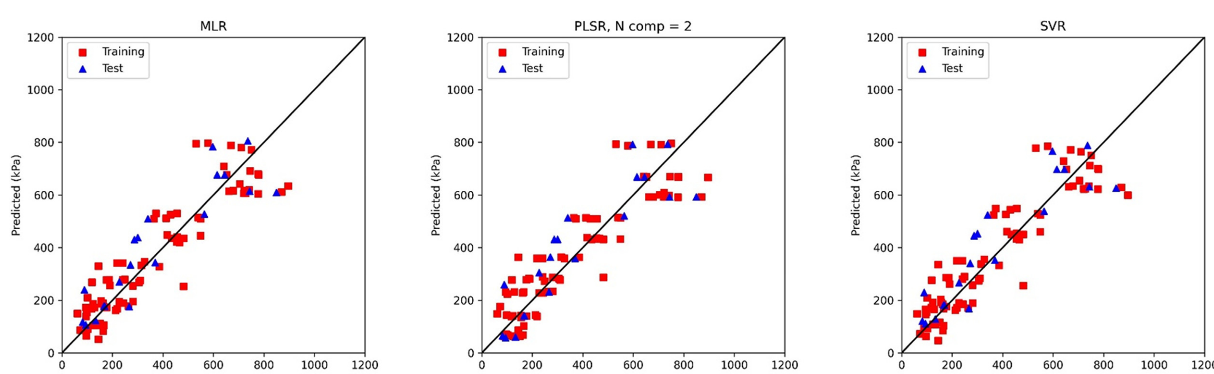

Fig. 10. Scatter plots of actual and predicted bio-yield stress by models.

Table 1. Evaluation results of onion quality prediction models.

Method	Quality	R^2		RMSE (kPa)		MAPE (%)	
		Train	Test	Train	Test	Train	Test
MLR	Bio-yield Stress	0.836	0.8029	96.87	106.7	28.47	29.12
PLSR	Bio-yield Stress	0.8221	0.7773	101.3	113.4	32.78	33.87
SVR	Bio-yield Stress	0.8375	0.8053	96.41	106.1	28.68	25.86

PLSR, the lowest among the three models. These results are interpreted as PLSR, which converts multivariate data into small number of latent variables for regression, is less suitable in our model in which only three variables are used as input. Similar values were shown in R^2 and RMSE of MLR and SVM, indicating that optimized model can be obtained only with linear regression. In the case of MAPE, SVR showed lower value than that of MLR, which is considered because the error of SVR appeared relatively low in the region where the values of the dependent variables were high. Fig. 10 shows scatter plots of actual and predicted bio-yield stress of trained machine learning models. Models generally showed similar trends, and the error increased in the data in the high bio-yield stress range.

Conclusions

In the experiment of this study, environmental data including temperature and relative humidity, and onion physical properties including weight, bio-yield stress, and onion respiration rate were measured. For prediction of onion quality using environmental data, three different models were built to predict bio-yield stress for onion during storage. PLSR was trained using 2 latent variables to build the models, and SVR was trained using the best hyperparameters of C, g and ε and RBF kernel. The models were evaluated by calculating the evaluation metrics including R^2, RMSE, and MAPE. In the measurement data, the bio-yield stress showed decreasing trend. On the other hand, the weight loss was increased along with storage time, and the respiration rate was increased until 7 weeks, and a sudden drop happened in the 8^{th} week. For the prediction of bio-yield stress of onion, we found that SVR and MLR could be used to predict the quality attributes of onion during storage with R^2 values of > 0.8.

In this study, quality change results during storage of onion and models for predicting onion quality are presented. Although the modeling results showed the correlation between environmental data and onion quality, there is a limitation that the experiment was conducted for one condition and the data from one experimental batch was used for modeling. Since correlation between data exists within one batch of time series data, it is considered that additional experiments with various storage condition and appropriate dataset splits are required in further research for training and evaluation of robust models.

Acknowledgements

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