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Predicting postharvest weight loss and texture changes in table grapes using fruit color and machine learning

Xiaoyan Cheng [a,*], Yao Zhou [a], Zhengyang Huo [a], Ruiying Li [a], Shiqian Xu [b], Hao Qi [b], Jianyuan Zhu [b], Fei Wang [a], Yang Bi [c,*]

[a] College of Science, Gansu Agricultural University / State Key Laboratory of Aridland Crop Science, Co-Built by the Provincial and Ministerial Authorities, Lanzhou 730070, China

[b] College of Information Science and Technology, Gansu Agricultural University, Lanzhou 730070, China

[c] College of Food Science and Engineering, Gansu Agricultural University, Lanzhou 730070, China

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A B S T R A C T

Accurately predicting postharvest quality is crucial for optimizing storage and reducing losses in table grapes. This study explores the potential of fruit color parameters as non-invasive indicators of postharvest weight loss and textural changes. Using convolutional neural networks (CNNs), we developed predictive models based on colorimetric data, achieving high accuracy ($R^2 > 0.80$ for weight loss and $R^2 > 0.97$ for texture). Additionally, the effects of storage temperature on grape quality were examined, revealing that colder storage at 3°C significantly reduces weight loss and maintains texture better than storage at 10°C. Among tested cultivars, 'Shine Muscat' exhibited lower weight loss and superior textural stability compared to 'Flame Seedless'. These findings highlight the potential of integrating color-based assessments and machine learning models into postharvest monitoring, offering a practical approach for improving quality control and storage management in the grape industry.

1. Introduction

Postharvest losses have a significantly impact on the global fruit industry, with quality deterioration during storage posing a major challenge for producers and retailers (Ali et al., 2025). Table grapes, in particular, are highly perishable, with postharvest weight loss and texture degradation being key factors affecting marketability (Blanckenberg et al., 2021). These quality changes are influenced by factors such as temperature, humidity, and grape cultivar characteristics (Owoyemi et al., 2024; Moradi et al., 2024). To extend shelf life and maintain fruit quality, effective storage strategies and innovative quality assessment methods are essential.

Traditional methods for evaluating postharvest quality rely on destructive techniques, such as weight measurement and texture analysis, which are time-consuming, labor-intensive, and impractical for large-scale applications (Ktenioudaki et al., 2021; Oh et al., 2024). Recently, non-destructive approaches, including imaging technology and spectral analysis, have gained attention for their ability to monitor fruit quality in real time (Ali et al., 2023; Shen et al., 2024; Shen et al., 2024). Among these, fruit color parameters have shown promise as indicators of postharvest changes, as color variations are often associated with physiological alterations such as dehydration, pigment degradation, and cell wall breakdown (Wang et al., 2023). Advanced colorimetric techniques offer an opportunity for rapid, non-invasive assessment, providing valuable information for optimizing storage and reducing postharvest losses (Palumbo et al., 2023).

Machine learning techniques, particularly convolutional neural networks (CNNs), have emerged as powerful tools for predictive modeling in agricultural sciences (Liu et al., 2021; Peng et al., 2024). These models can process large datasets, recognize complex patterns, and provide accurate predictions, making them ideal for assessing postharvest fruit quality. By using image-based data, CNNs can detect subtle color changes that may not be visible to the human eye, enabling precise predictions of postharvest deterioration (Ali et al., 2024; Ko et al., 2021). The application of such models in the fruit industry has the potential to improve decision making, optimize storage protocols and increase overall supply chain efficiency.

This study aims to explore the feasibility of using fruit color parameters in combination with machine learning models to predict postharvest weight loss and texture changes in table grapes. Specifically,

* Corresponding authors.
E-mail addresses: chengxy@gsau.edu.cn (X. Cheng), biyang@gsau.edu.cn (Y. Bi).

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we investigate how colorimetric features correlate with physical changes in grape quality and assess the impact of different storage temperatures on postharvest deterioration. By integrating non-destructive color assessment with machine learning models, this research provides insights into practical, scalable solutions for post-harvest monitoring, offering a novel approach to improving quality control and storage management in the grape industry.

2. Materials and methods

2.1. Grape samples and treatments

Two grape cultivars, 'Flame Seedless' and 'Shine Muscat', were selected to represent the distinct physiological and commercial types commonly found in Asian markets. 'Flame Seedless' is a widely available red variety with moderate storage stability, while 'Shine Muscat' is a premium green variety noted for its firmness and long shelf life. These contrasting characteristics enabled a comparative evaluation of the robustness of the predictive model across different textural and physiological profiles. 'Flame Seedless' with red skin and 'Shine Muscat' with green skin, were harvested at commercial maturity from the vineyard of Gansu Agricultural University. The selection of samples adhered to strict criteria. Only grapes with uniform size (transverse diameter within 14 mm - 16 mm for 'Flame Seedless' and 22 mm - 24 mm for 'Shine Muscat'), had a bright and typical skin color for each cultivar, had intact green stems, and were free from any visible mechanical damage were chosen. A taste test was also conducted to ensure that the grapes had a moderate balance of sweetness (16 °Bx - 18 °Bx for 'Flame Seedless' and 18 °Bx - 20 °Bx for 'Shine Muscat') and acidity (titratable acidity of 0.4 % - 0.6 % for both cultivars), aiming to maintain consistent initial quality. All grapes were harvested from the same vineyard block to minimize the influence of different growing environments. After harvesting, the grapes were immediately packed into polyethylene baskets (produced by Yuanzhibo Plastic Technology Co., Ltd, Chongqing, China) lined with 0.1 mm thick plastic bags (manufactured by Jiamei Huanyu Technology Co., LTD, Beijing, China), measuring 80 cm × 100 cm. The samples were then stored at two different temperatures (3°C and 10°C) and a relative humidity (RH) ranging from 85 % - 90 % to simulate common postharvest storage conditions in the industry. One thousand berries were prepared for each treatment. While the study focused on a single harvest population to ensure controlled experimental conditions, the selected storage temperatures and humidity levels selected were chosen to reflect typical postharvest handling practices, thereby enhancing the practical relevance of the findings.

2.2. Weight loss measurement

The gravimetric method was adopted to measure the weight loss of grapes during storage. A precision digital balance (XK3190-A12+E, Zanwei Weighing Instrument Co., Ltd, Shanghai, China) with a readability of 0.01 g was used for this purpose. The percentage of weight loss (w) was calculated using the following formula:

$$w = \frac{w_0 - w_1}{w_0} \times 100\% \tag{1}$$

Where w_0 represents the initial weight of the grape samples at the beginning of storage, and w_1 is the weight of the samples after a certain storage time. To ensure accuracy, weight measurements were conducted every day, and each treatment group (each cultivar at each storage temperature) was measured in triplicate.

2.3. Color measurement

Fruit color was assessed using a handheld reflectance colorimeter (Three Enshi Technology Co., Ltd, Shenzhen, China) operating in CIE $L^*a^*b^*$ color space. Color measurements were taken before and during the cold storage at 1-day intervals for 15 days. Before each measurement, the instrument was calibrated with a white reference tile and set to the standard illuminant D65, which has a correlated color temperature of approximately 6500K. Color values (L^*, a^*, b^*, C, H) were recorded at three equidistant points on each bunch. There were three replicates of ten berries per each treatment and per cultivar. The total number of measurements was 30 per treatment for each cultivar.

2.4. Texture analysis

The texture properties of the berries, including hardness and brittleness, were measured using a texture analyzer (TA.XT Express, Stable Micro Systems, UK) equipped with a P/2 probe (2 mm diameter). Test parameters were set as follows: a compression distance of 10.0 mm, a pre-test speed of 1.00 mm/s, a test speed of 1.00 mm/s, and a post-test speed of 1.00 mm/s. These were set in accordance with the methodology described by Balic et al. (2022). Three replicates were performed for each treatment, with a total of 30 measurements taken for each cultivar to ensure the reproducibility. These parameters were based on previous research and optimized to accurately capture the texture characteristics of the table grapes under study.

2.5. Statistical analysis

All experimental data were analyzed using Origin 2021 software (OriginLab Corporation, Northampton, MA, USA). Pearson correlation analysis was employed to assess the relationships between fruit color, weight loss, and texture parameters. The significance level was set at $p < 0.01$, meaning that only correlations with a probability of less than 1 % of occurring by chance were considered statistically significant. This strict significance level helps to ensure the reliability and validity of the identified correlations.

2.6. Predictive modeling and machine learning

Predictive models were developed with the aim of describing the changes in fruit quality attributes over storage time. Different types of models were applied based on the characteristics of the variables:

Logistic model: This model was used to describe the changes in L^*, a^*, b^*, and C values. These color parameters often exhibit non-linear growth patterns during storage, and the logistic model is well suited to capture such S-shaped curves.

Linear model: This model was applied to analyze the trends in H value and berry hardness. When the changes in these variables over time are consistent enough to be approximated by a straight line, the linear model provides a simple and effective way to describe their relationships.

Exponential models: The ExpDec1 and ExpGrow1 models were utilized to characterize the changes of weight loss and berry brittleness, respectively. Weight loss often follows an exponential decay pattern as the grapes lose moisture over time, while brittleness may show exponential growth or decay depending on the physiological changes in the fruit.

Convolutional Neural Networks (CNNs) were employed to predict weight loss and texture based on fruit color data. The architecture of the CNN model was designed as follows:

Input Layer: The input layer received color parameters (L^*, a^*, b^*, C, H), which served as the features for the model to learn from.

Hidden Layer: The hidden layer consisted of 10 neurons with ReLU (Rectified Linear Unit) activation function. The ReLU function helps to introduce non-linearity into the model, enabling it to learn complex relationships in the data. The Adam optimizer was used to optimize the model, with a learning rate set at 0.001. This optimizer adaptively adjusts the learning rate for each parameter during training, improving the convergence speed and stability of the model.

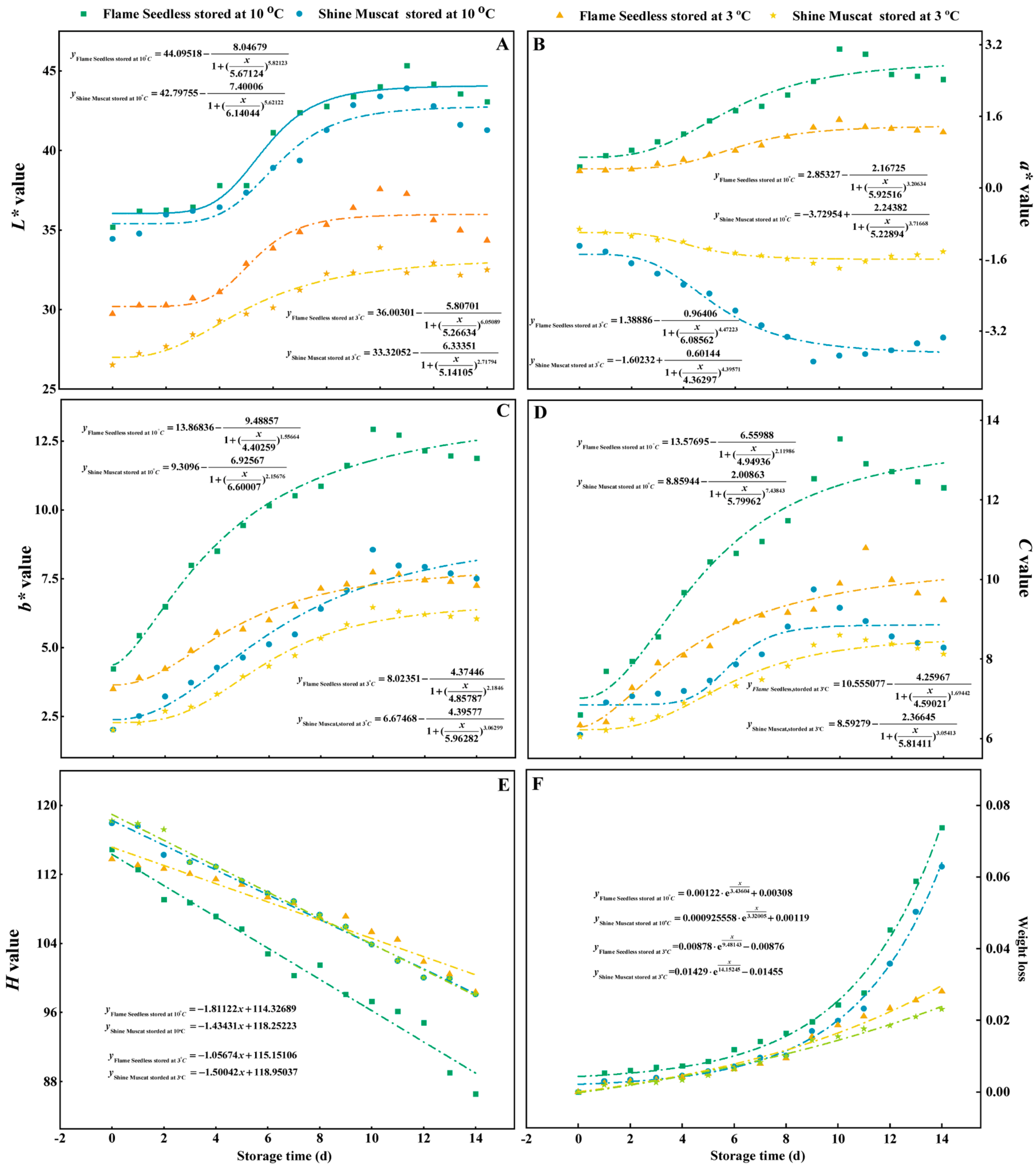

Fig. 1. Changes in color parameters (L^* (A), a^* (B), b^* (C), C (D), H (E)) and weight loss (F) of 'Flame Seedless' and 'Shine Muscat' berries during 15 days of storage, with corresponding regression models for trend analysis.

Output Layer: Predictions for weight loss, hardness, and brittleness

The output layer generated predictions for weight loss, berries hardness, and berries brittleness.

The predictive performance of the models was evaluated using several metrics, including the coefficient of determination (R^2, $R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$), root mean square error (RMSE, $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$), and the loss function (Loss, $\text{Loss} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$). The R^2value indicates the proportion of the variance in the dependent variable that is predictable from the independent variables, with values closer to 1 indicating a better fit. The RMSE measures the average magnitude of the errors in the predictions, and a lower RMSE value implies more accurate predictions. The loss function was minimized during the training process to optimize the model's performance. To ensure the robustness of the models and mitigate the issue of overfitting, cross-validation was performed (Tempelaere et al., 2023; Singh et al., 2024). Cross-validation involves splitting the data into training and validation sets multiple times, training the model on the training set, and evaluating it on the validation set. This process helps to assess how well the model generalizes to new, unseen data, improving the reliability of the model's predictions.

In addition, decision trees were used to analyze the importance of the input variables (color parameters) on the weight loss and texture of table grapes. By examining the structure and splits of the decision trees, the relative importance of each color parameter can be determined. Based on this analysis, regression prediction surfaces were constructed under different tree depths. The optimal tree depth was determined by considering the training error, test error, and cross-verification error. This approach helps to find the most appropriate level of complexity for

Table 1
The CV confidence intervals of the model fit coefficients and the R^2 of the fitted model for color parameters (L^*, a^*, b^*, C, H) and weight loss in berries.

Parameters	Cultivars	Temperature	The confidence interval of CV	R^2
L^*	Flame Seedless	10°C	[0.008933, 0.092179]	0.96716
		3 °C	[0.012353, 0.136446]	0.90632
	Shine Muscat	10 °C	[0.014109, 0.073793]	0.96716
		3 °C	[0.016182, 0.128798]	0.94537
a^*	Flame Seedless	10°C	[0.105359, 0.142519]	0.91736
		3 °C	[0.058576, 0.133192]	0.9494
	Shine Muscat	10°C	[-0.090575, 0.298021]	0.95512
		3 °C	[-0.065832, 0.129657]	0.87472
b^*	Flame Seedless	10°C	[0.0835059, 0.242522]	0.97354
		3 °C	[0.0533818, 0.245042]	0.97247
	Shine Muscat	10°C	[0.1619392, 0.366156]	0.95096
		3 °C	[0.0522137, 0.212727]	0.97888
C	Flame Seedless	10°C	[0.0660604, 0.324871]	0.95369
		3 °C	[0.0580206, 0.421208]	0.92530
	Shine Muscat	10°C	[0.0258695, 0.426348]	0.85391
		3 °C	[0.0326203, 0.328797]	0.95036
H	Flame Seedless	10°C	[-0.046896, 0.006111]	0.9722
		3 °C	[-0.059731, 0.004508]	0.95568
	Shine Muscat	10°C	[-0.025573, 0.002552]	0.99157
		3 °C	[-0.025592, 0.002655]	0.99156
Weight loss	Flame Seedless	10°C	[-0.076591, 0.457792]	0.98943
		3 °C	[-0.223941, 0.437357]	0.97751
	Shine Muscat	10°C	[-0.047975, 0.244312]	0.99374
		3 °C	[-0.461168, 0.438698]	0.98433

the decision tree model, balancing between underfitting and overfitting.

3. Results

3.1. Changes in fruit color and weight loss

During storage, the color of 'Flame Seedless' and 'Shine Muscat' grapes changed dynamically, showing different trends at 3°C and 10°C (Fig. 1, Table 1). Specifically, the L^* value, which represents lightness, remained stable for the first three days, after which it increased as the grapes ripened further, reaching a peak around the 9th day of storage at 10°C, while at 3°C, this peak occurred slightly later, on the 11th day. Subsequently, as storage time increased, the L^* value gradually declined. By the 15th day of storage, the L^* value of grapes stored at 10°C decreased by 9.09 % compared to the peak value, while that of grapes stored at 3°C only decreased by 6.25 %. This suggests that higher temperatures accelerate the degradation of grape lightness. The a^* value (related to redness-greenness), showed the same trend as L^* in 'Flame Seedless', while it showed a progressively decreasing trend in 'Shine Muscat'. The b^* value (related to yellowness-blueness) showed an increasing trend during storage at 10°C and 3°C in the two cultivars, reaching a peak on the 11th day. C values increased quickly in 'Flame Seedless' at 10°C, while at 3°C, they remained stable for the initial four days and then increased slowly and finally stabilized. For the 'Shine Muscat' at 10°C and 3°C, C values rose slowly during the initial 8 days and stabilized at mid-storage period before gradually declining after prolonged storage. These changes in a^*, b^*, and C values collectively reflected the evolution of grape color. The more significant changes at 10°C indicated greater color degradation under higher temperature conditions. In contrast, the H value (hue angle) showed a continuous decrease throughout the storage period. Within 15 days of storage, the H value decreased by 25 % and 15 % compared to the initial value for 'Flame Seedless' and 'Shine Muscat', respectively. This change in the H value suggested a shift in the hue of the grapes, with 'Shine Muscat' demonstrating superior color stability compared to 'Flame Seedless', especially at 3°C, as its color parameters showed less variation. In term of weight loss, there was a slight increase in the first 9 days and then increased quickly as the storage time extended. At 3°C, the daily average weight loss rate of 'Flame Seedless' was 0.2 %, while at 10°C, it reached 0.5 %. At 10°C temperature, the increment became much more rapid after 10 days of storage. 'Shine Muscat' showed a lower weight loss, experiencing a weight loss of 6.2 % at 10°C and 2.8 % at 3°C (Fig. 1 F). The logistic model was applied to describe the changes in L^*, a^*, b^*, and C values. Its high coefficient of determination ($R^2 > 0.85$) and low coefficient of variation ($|CV| < 0.5$) indicated a good fit. The linear model effectively represented the H value trend, and the exponential model accurately described the weight loss trend. This further validates the reliability of these models in characterizing the changes in fruit color and weight loss.

3.2. Texture changes

Both hardness and brittleness of the two grape cultivars decreased significantly during storage, with the rate of decline was closely related to the storage temperature (Fig. 2). At 10°C, the hardness of 'Flame Seedless' and 'Shine Muscat' decreased by 46.93 % and 38.59 %, respectively, within 15 days. At 3°C, the hardness decreased to 340 N

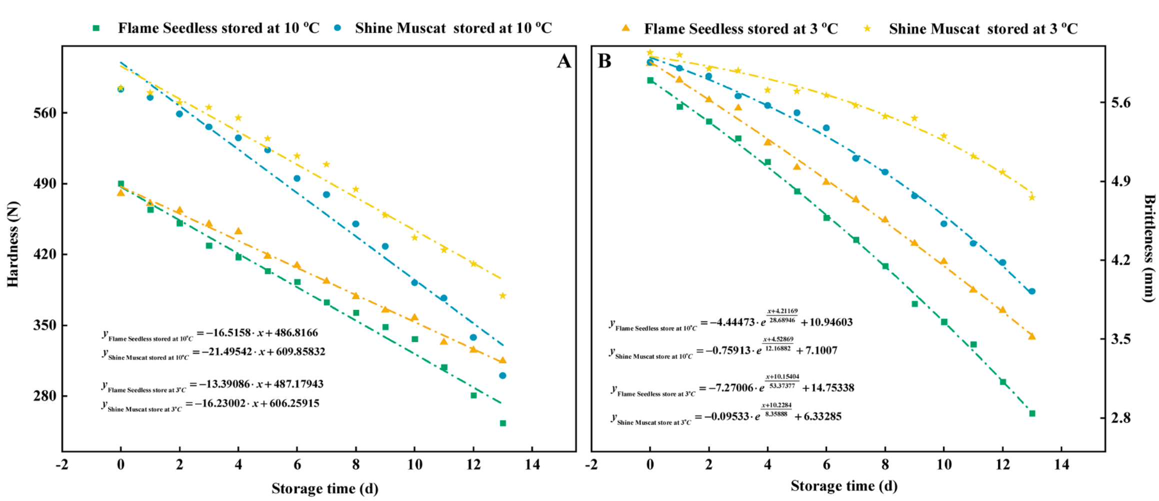

Fig. 2. Changes in hardness (A) and brittleness (B) of 'Flame Seedless' and 'Shine Muscat' berries during storage, with corresponding predictive models.

Table 2
The CV confidence intervals of the model fit coefficients and the R^2 of the fitted model for berry hardness and brittleness.

Parameters	Cultivars	Temperature	The confidence interval of CV	R^2
Hardness	Flame Seedless	10 °C	[-0.036215, 0.00939]	0.98451
		3 °C	[-0.220643, 0.004638]	0.99419
	Shine Muscat	10 °C	[-0.052713, 0.014211]	0.96773
		3 °C	[-0.047919, 0.009812]	0.97318
Brittleness	Flame Seedless	10 °C	[-0.071333, 0.209408]	0.99832
		3 °C	[-0.079723, 0.471801]	0.99751
	Shine Muscat	10 °C	[-0.118979, 0.016403]	0.99582
		3 °C	[-0.139829, 0.024117]	0.98638

and 390 N, representing reduction of 30.61 % and 27.83 %, respectively. These data clearly showed that colder storage at 3°C preserved the textural quality of both cultivars better than storage at 10°C, reducing the loss of hardness by approximately 11 % - 15 %. Similar trends were observed in terms of brittleness. The initial brittleness value of ‘Flame Seedless’ was 5.6 N, decreasing to 2.8 N at 10°C within 15 days (a 50.0 % decrease). At 3°C, the value increased to 3.5 N (a 37.5 % decrease). ‘Shine Muscat’ showed better resistance to textural degradation, with their brittleness decreasing from 5.7 N to 4.0 N at 10°C (a 29.8 % decrease) and to 4.8 N at 3°C (a 15.8 % decrease). The linear model for hardness and the exponential model for brittleness both achieved high predictive accuracy ($R^2 > 0.96$, $|CV| < 0.5$, Table 2), successfully capturing the texture change patterns over time and further highlighting the significant impact of storage temperature and grape variety on these changes.

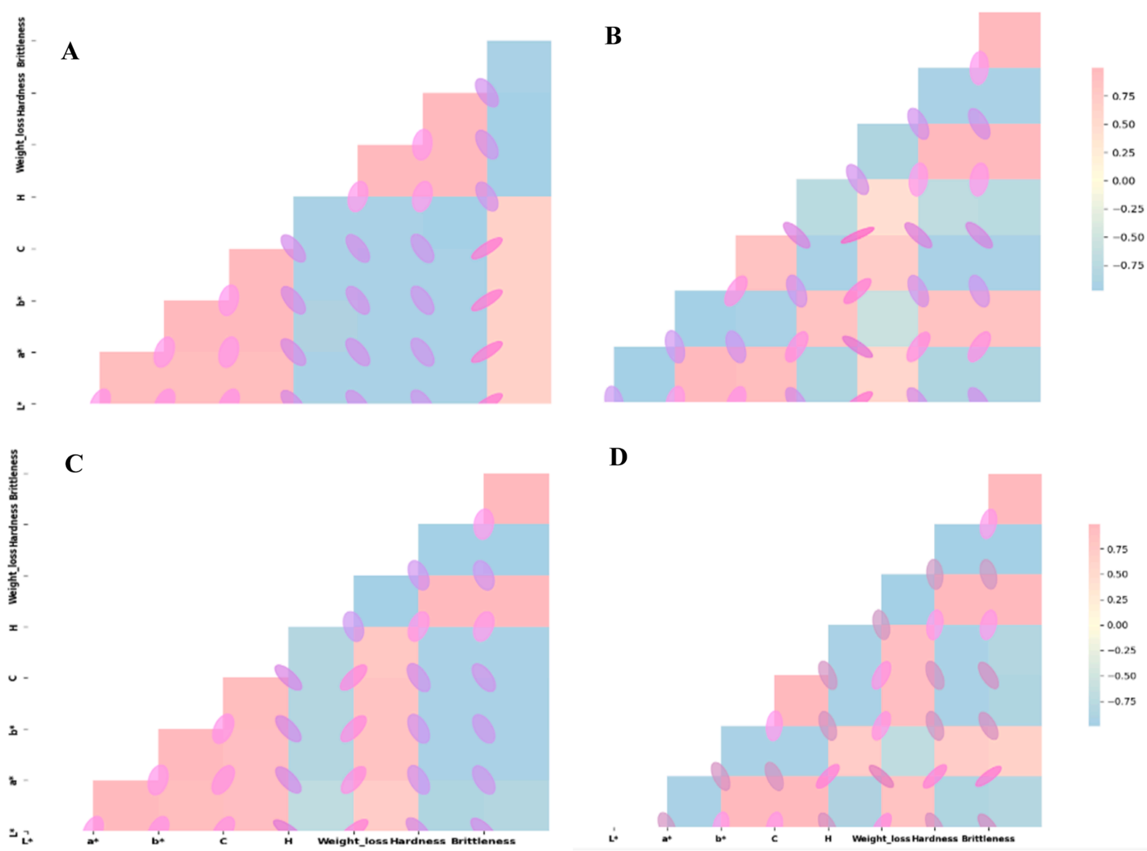

Fig. 3. Pearson’s correlation coefficients between color parameters (*L*, a*, b*, C, H*), weight loss, hardness, and brittleness in ‘Flame Seedless’ and ‘Shine Muscat’ berries stored at 10°C (A, C) and 3°C (B, D), with significant correlations indicated at $p < 0.01$.

Table 3
Pearson correlation coefficients between fruit color parameters (*L*, a*, b*, C, H*), weight loss and texture (hardness, brittleness) of ‘Flame Seedless’ (marked in black) and ‘Shine Muscat’ (marked in gray) at 10°C.

	*L**	*a**	*b**	*C*	*H*	Weight Loss	Hardness	Brittleness
L*		0.96	0.95	0.96	-0.73	0.76	-0.87	-0.85
a*	-0.98		0.98	0.93	-0.85	0.88	-0.94	-0.93
b*	0.98	-0.97		0.97	-0.85	0.85	-0.95	-0.94
C	0.95	- 0.96	0.91		-0.81	0.82	-0.92	-0.91
H	-0.91	0.90	-0.95	-0.79		-0.98	0.97	0.97
Weight Loss	0.64	-0.63	0.73	0.49	-0.88		-0.96	-0.97
Hardness	-0.88	0.87	-0.93	-0.76	0.99	-0.92		0.99
Brittleness	-0.90	0.89	-0.94	-0.77	0.99	-0.90	0.99	

Table 4
Pearson correlation coefficients between fruit color parameters (L^*, a^*, b^*, C, H), weight loss and texture (hardness, brittleness) of 'Flame Seedless' (marked in black) and 'Shine Muscat' (marked in gray) at 3°C.

	L^*	a^*	b^*	C	H	Weight Loss	Hardness	Brittleness
L^*		-0.98	0.98	0.95	-0.91	0.64	-0.88	-0.90
a^*	-0.95		-0.97	-0.96	0.90	-0.63	0.87	0.89
b^*	0.98	-0.93		0.91	-0.95	0.73	-0.93	-0.94
C	0.98	-0.94	0.99		-0.79	0.49	-0.76	-0.77
H	-0.92	0.80	-0.96	-0.94		-0.88	0.99	0.99
Weight Loss	0.88	-0.74	0.93	0.91	-0.98		-0.92	-0.90
Hardness	-0.90	0.77	-0.95	-0.93	0.99	-0.99		0.99
Brittleness	-0.85	0.69	-0.90	-0.88	0.98	-0.98	0.98	

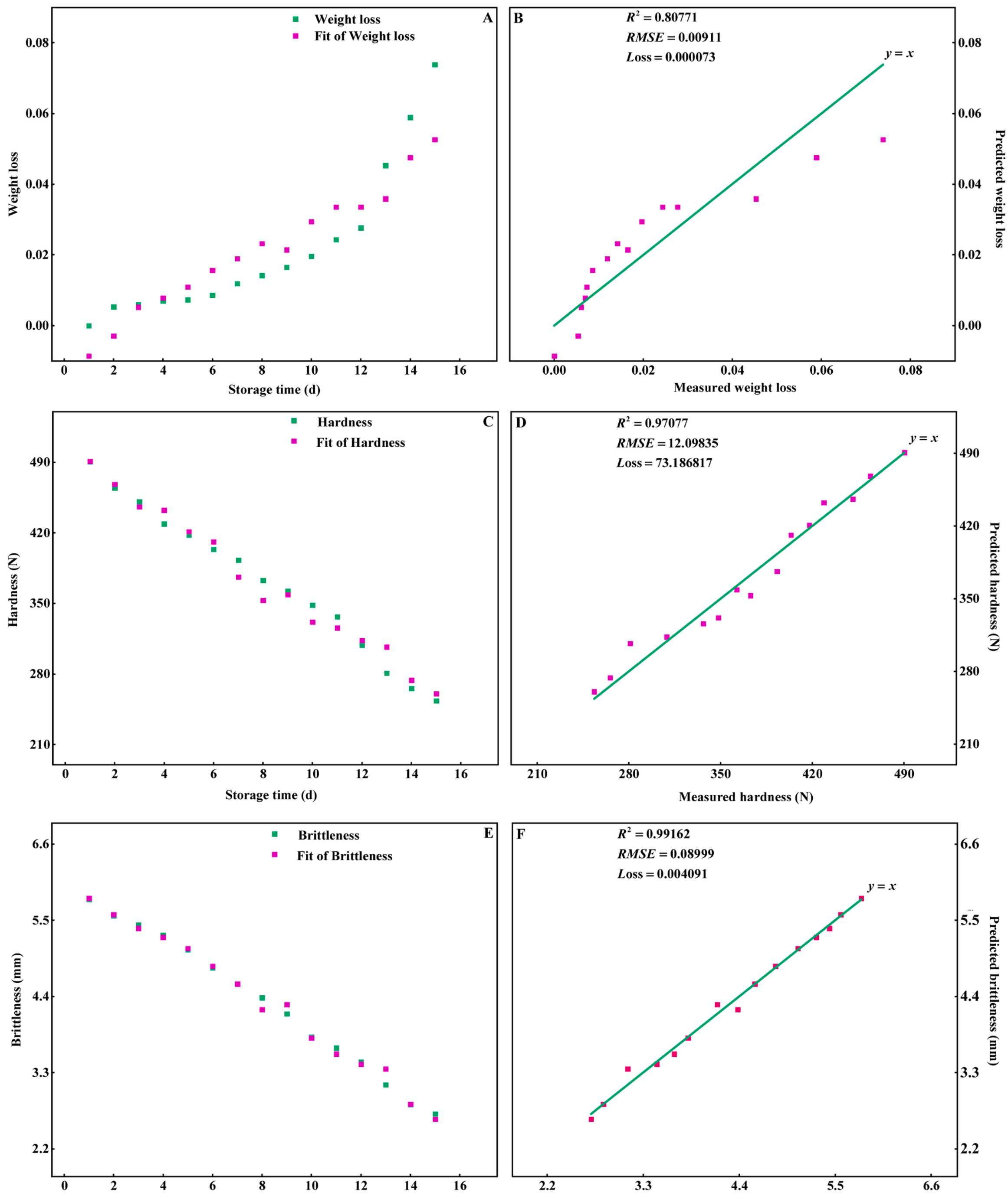

Fig. 4. Fitting and prediction of weight loss (A, B), hardness (C, D) and brittleness (E, F) in 'Flame Seedless' berries stored at 10°C, with R^2, RMSE and loss values indicated in each subgraph.

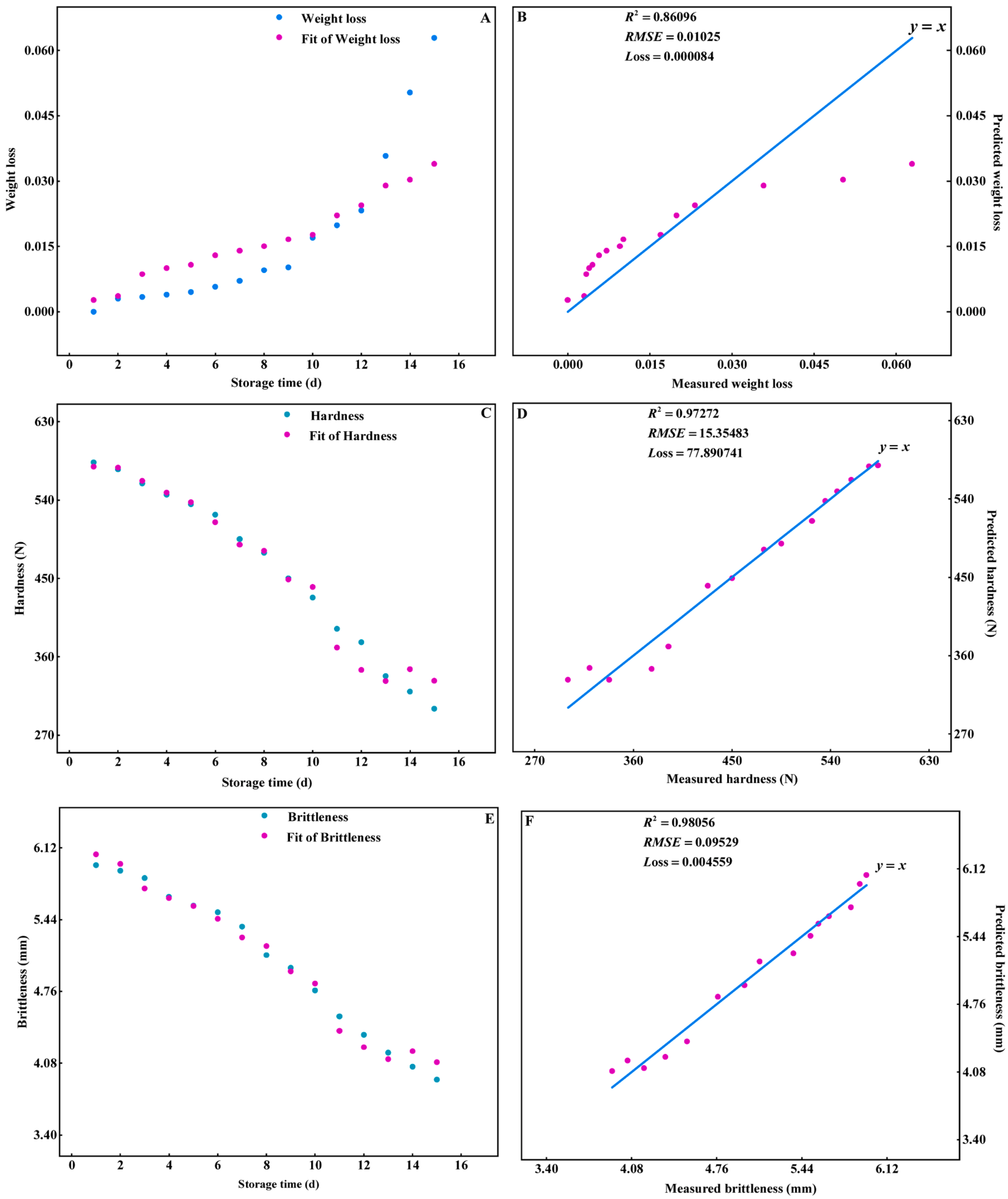

Fig. 5. Fitting and prediction of weight loss (A, B), hardness (C, D) and brittleness (E, F) in 'Shine Muscat' berries stored at 10°C, with R^2, RMSE and loss values indicated in each subgraph.

3.3. Correlation between fruit color, weight loss, and texture

Significant correlations were found among berry color parameters, weight loss, and texture. The L^*, a^*, b^*, and C values showed strong positive correlations with weight loss. The correlation coefficient between the L^* value and the weight loss of 'Flame Seedless' grapes was 0.89 (*p* < *0.01*), indicating that weight loss showed a corresponding change trend as the L^* value changed during storage. At the same time, these color parameters exhibited negative correlations with berry hardness and brittleness (Fig. 3). The correlation coefficients between the a^* value and berry hardness were - 0.98 and -0.95 for 'Flame Seedless' and 'Shine Muscat' ($p < 0.01$), respectively, meaning that an increase in the a^* value was accompanied by a decrease in berry hardness. Conversely, the H value was negatively correlated with weight loss but positively correlated with berry hardness and brittleness. The correlation coefficient between the H value and weight loss of 'Shine Muscat' grapes was - 0.98 ($p < 0.01$), while the correlation coefficients between the H value, hardness and brittleness were 0.99 and 0.98 ($p < 0.01$). The strong inverse relationship between weight loss and textural parameters, with correlation coefficients of - 0.99 for hardness and - 0.98 for brittleness in 'Flame Seedless', clearly demonstrated that moisture retention played a crucial role in maintaining the textural quality of grapes. These correlation results provided important theoretical support for understanding the internal relationships among the

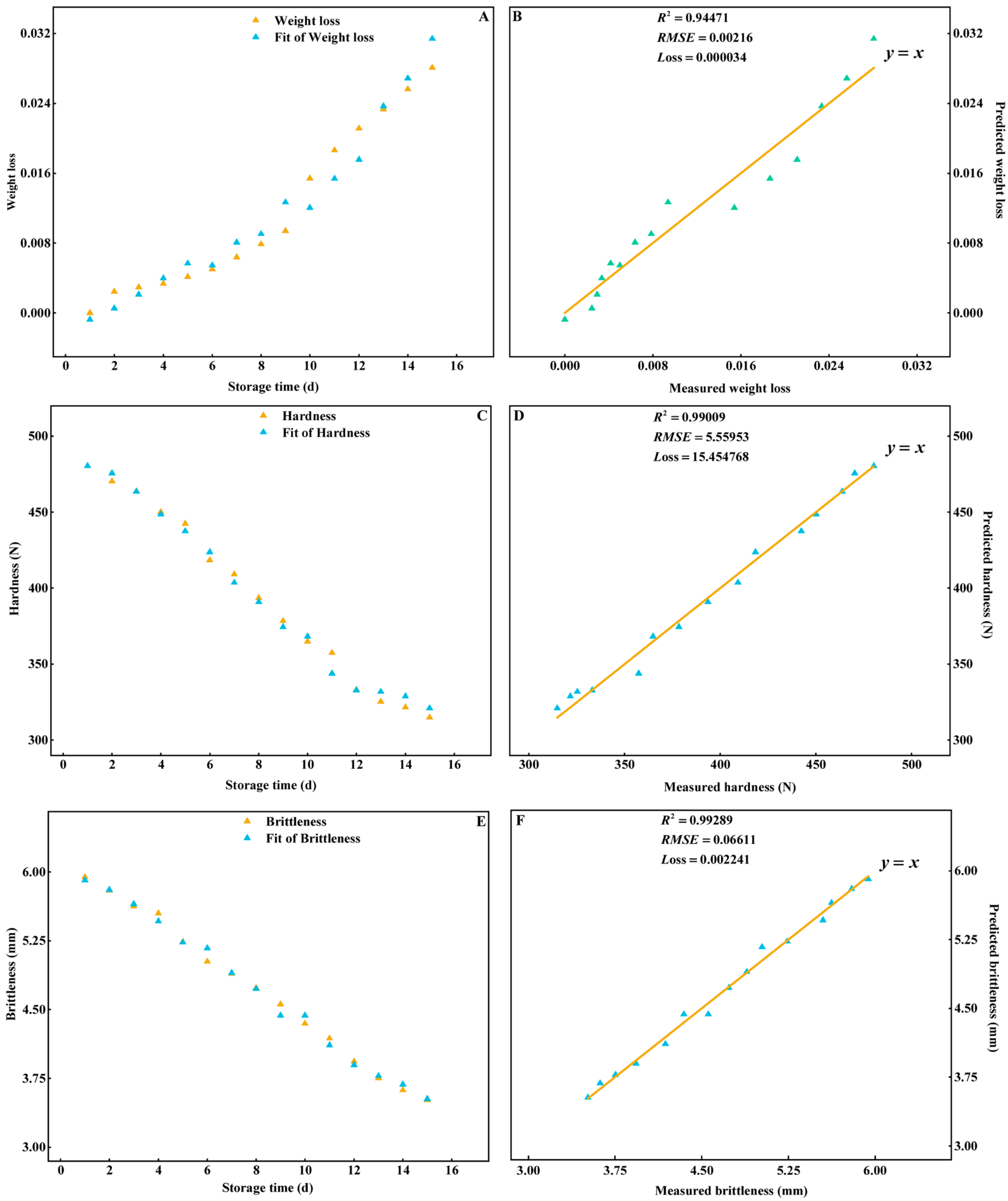

Fig. 6. Fitting and prediction of weight loss (A, B), hardness (C, D) and brittleness (E, F) of 'Flame Seedless' berries stored at 3°C, with R^2, RMSE and loss values indicated in each subgraph.

different postharvest quality attributes of grapes (Tables 3, 4).

3.4. Predictive modeling performance

The neural network regression models showed high predictive accuracy for weight loss, hardness, and brittleness under storage conditions of both 3°C and 10°C (Figs. 4–7). For weight loss prediction, at 3°C, the R^2 value of the model for 'Flame Seedless' was greater than 0.94, at 10°C, it was greater than 0.80. For hardness prediction, the R^2 values were 0.99 and 0.97 for 'Shine Muscat' at 3°C and 10°C, respectively. Similarly, for brittleness prediction, the R^2 values also reached highly 0.97 at 3°C and 10°C in two cultivars. The importance scores of the input variables (color parameters L^*, a^*, b^*, C, and H) indicated that the H value had the highest importance score of 0.84747162, followed by C (0.13291908), a^* (0.01333084), L^* (0.0042413), and b^* (0.00203715) (Fig. 8). This showed that the H value played a relatively more important role in the prediction process. Moreover, the models performed better at 3°C than at 10°C, which was consistent with the more stable changes in fruit quality attributes observed at lower temperatures. These results not only validated the feasibility of using fruit color as a non-invasive indicator for postharvest quality assessment but also highlighted the great potential of CNN-based models in real-time prediction of grape postharvest quality. This provides a new method and idea for managing grapes after harvest.

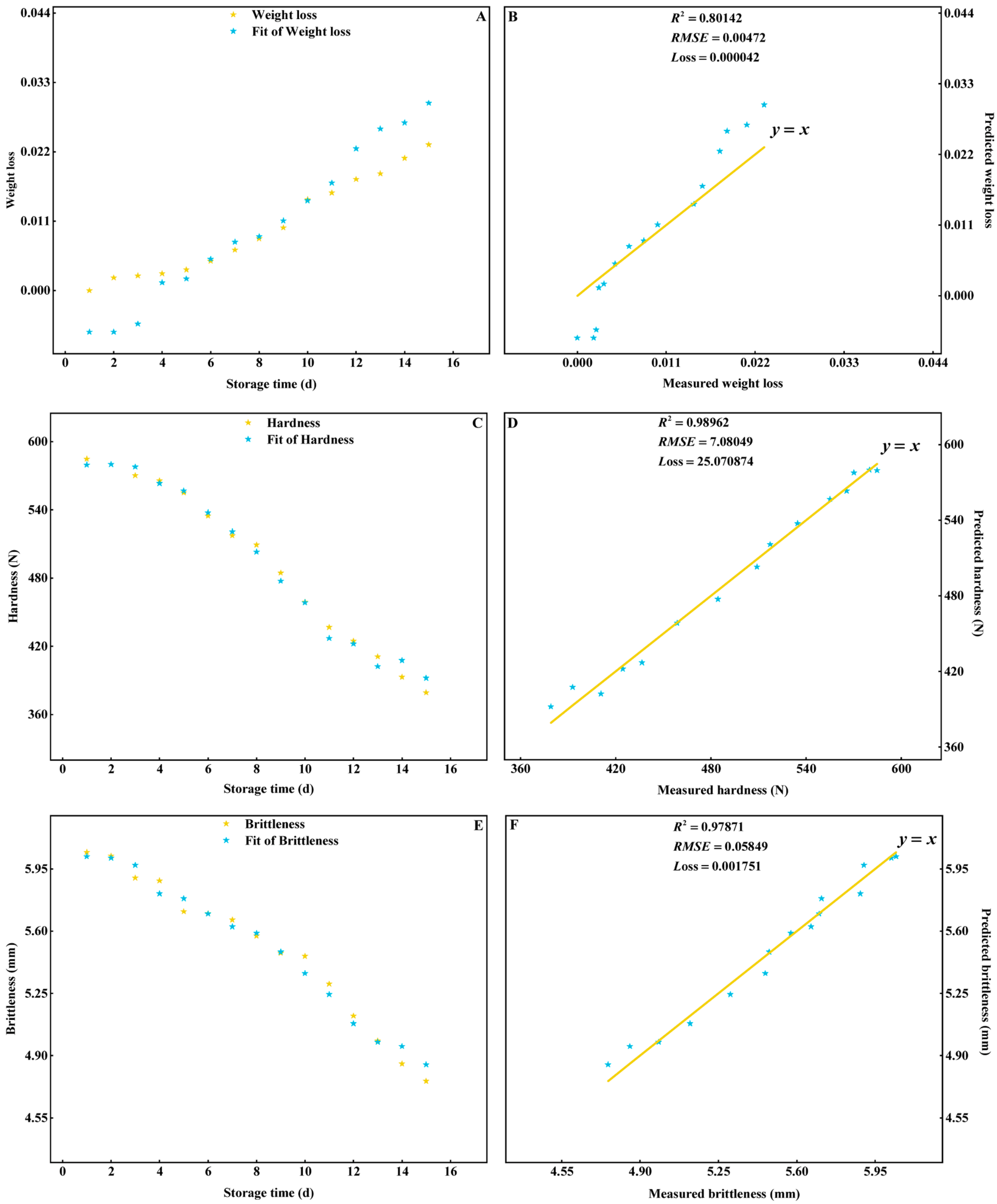

Fig. 7. Fitting and prediction of weight loss (A, B), hardness (C, D) and brittleness (E, F) of 'Shine Muscat' berries stored at 3°C, with R^2, RMSE and loss values indicated in each subgraph.

4. Discussion

The results of this study highlight the potential of fruit color parameters as non-invasive indicators for predicting weight loss and textural changes in table grapes during storage. This integrated approach represents a significant advance over traditional invasive methods is in line with the industry trend towards simplified and efficient quality assessment tools (Gómez et al., 2019; Wen et al., 2024).

4.1. Weight loss and storage temperature

Weight loss, primarily due to water loss through transpiration and carbon skeletons respiration, is a critical determinant of postharvest fruit quality (Gunny et al., 2024). The study confirmed that lower storage temperatures (3°C) significantly reduced weight loss compared to 10°C. These results are consistent with previous research showing that cold temperatures inhibit respiratory activities and enzymatic processes, thereby preserving moisture content (Cantín et al., 2020; Tongdeesoontorn, 2021; Pedrozo et al., 2024). The differences observed between the two cultivars, with 'Shine Muscat' exhibiting lower weight loss than 'Flame Seedless', could be attributed to structural factors such as thicker skins and higher moisture retention capacity (Romero et al., 2020).

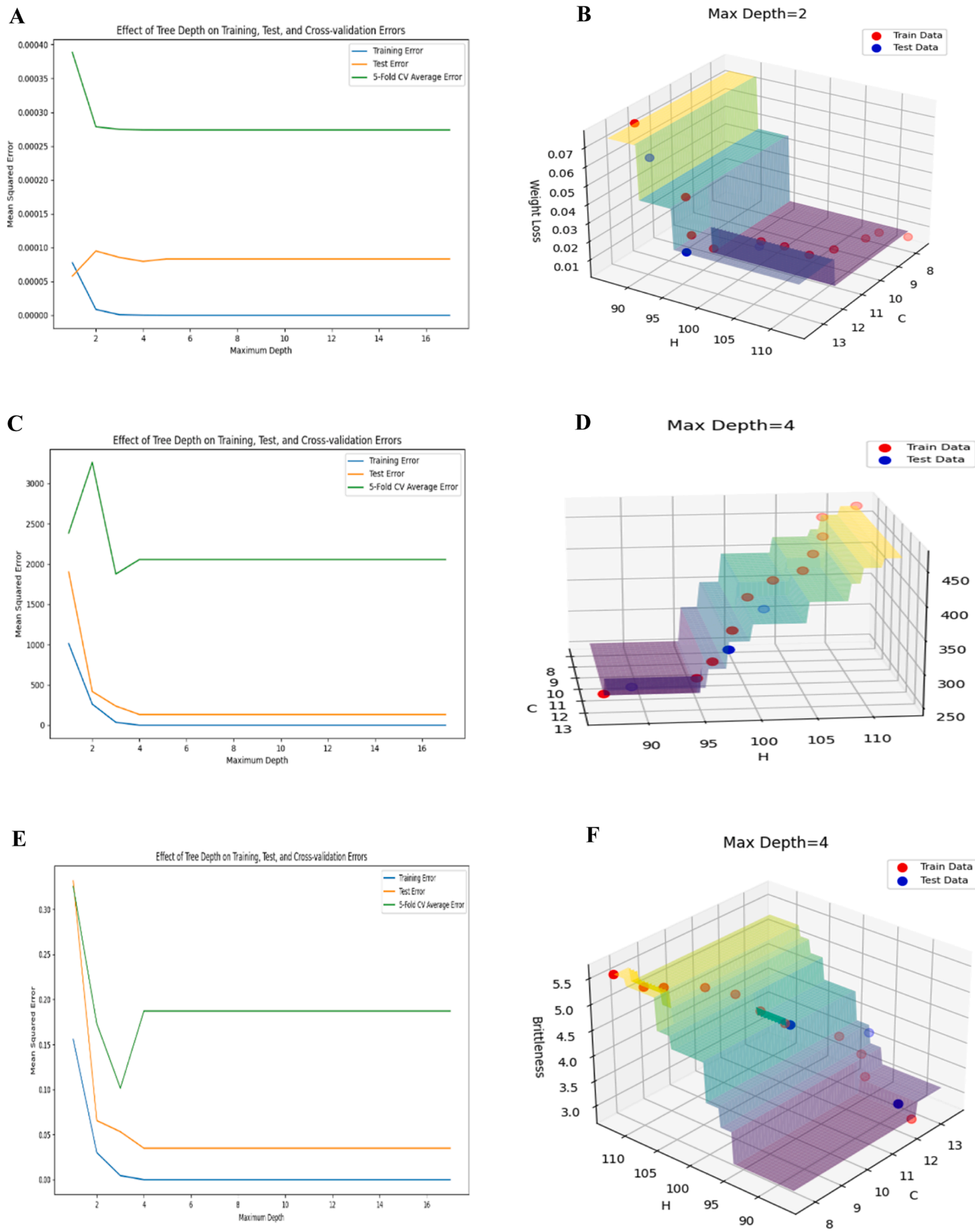

Fig. 8. Training error, test error, and 5-fold cross-validation test error for weight loss (A), hardness (C), and brittleness (E), alongside prediction regression surfaces of weight loss (B), hardness (D), and brittleness (F) under varying tree depths in decision tree models.

4.2. *Texture stability and cold storage*

Texture, represented by hardness and brittleness, is another critical quality attribute that affects consumer acceptance (Basile et al., 2022). This study showed that colder storage effectively slowed the degradation of texture, with reductions in hardness and brittleness being 11 % - 15 % lower at 3°C compared to 10°C. Similar findings have been reported for other fruits, where lower storage temperatures reduced the activity of cell wall-degrading enzymes and delayed the breakdown of pectin and cellulose (Ren et al., 2020; Tao et al., 2023). The better texture stability observed in 'Shine Muscat' further highlights the influence of cultivar-specific factors, such as cell wall mechanical strength and intercellular adhesion (Peña-Neira et al., 2023). While this study focused on external color and physical attributes, future work will incorporate internal quality parameters, such as TSS, TA and pH, to expand the predictive scope of the model and improve the robustness and practical applicability of the models in real-world postharvest scenarios. Combining image-based and chemical indicators could enhance the model's robustness and provide more effective support for commercial quality control practices.

4.3. Correlation among fruit color, weight loss, and texture

This study revealed significant correlations between fruit color parameters and physical attributes such as weight loss and texture. Positive correlations between L^*, a^*, b^*, and C values and weight loss, together with their negative correlations with hardness and brittleness, suggest that fruit color changes reflect underlying physiological processes (Li et al., 2024; Wang et al., 2024). These results confirm the potential of color as a proxy for monitoring some quality attributes, with H value emerging as a reliable indicator of both weight loss and texture changes during storage (Gao et al., 2019; Fu et al., 2024). The strong correlation between weight loss and texture degradation (r = -0.91 for hardness and r = -0.90 for brittleness) reinforces the central role of moisture retention in maintaining structural integrity.

4.4. Predictive modeling and practical implications

Although the predictive trends observed in this study are consistent with recognized postharvest behaviors, the innovation lies in achieving these results through the use of non-invasive color features and CNN-based models. This approach enables the real-time, scalable assessment of fruit quality, eliminating the need for destructive sampling and offering practical value for storage management and supply chain optimization. The neural network regression models developed in this study achieved high predictive accuracy, outperforming traditional regression methods. This demonstrates the ability of advanced machine learning techniques to integrate complex, nonlinear relationships among fruit quality attributes (Knott et al., 2023; Cheng et al., 2024). The predictive accuracies ($R^2 > 0.80$ across all models) indicate the robustness of the approach, although further validation on independent datasets and other cultivars is required to confirm generalizability.

The practical application of using handheld colorimeters for grape quality assessment is a significant step towards simplifying postharvest quality management. However, potential challenges such as equipment cost, calibration requirements, and user training need to be addressed to ensure widespread adoption. Additionally, integrating chemical analyses, such as sugar and acid content, with color-based predictions could further improve the accuracy and applicability of the model.

Despite the promising results, this study has several limitations. Firstly, the focus on only two grape cultivars and two storage temperatures restricts the generalizability of the results. Future studies should be expanded to include a broader range of cultivars and storage conditions. Secondly, the reliance on the same dataset for model training and testing raises concerns about overfitting. Independent validation and cross-validation should be performed to ensure model robustness. Finally, the exclusion of chemical quality attributes such as sugar, acid, and pectin content limits the scopes of the study. Inclusion of these parameters in future models could provide a more holistic understanding of postharvest grape quality. Future research will seek to validate CNN models using external datasets and a wider variety of grapes.

5. Conclusions

This study highlights the potential of fruit color parameters as non-invasive indicators for predicting weight loss and texture changes in table grapes during cold-storage. Neural network regression models achieved high predictive accuracies ($R^2 > 0.80$), offering a practical alternative to traditional invasive methods. Colder storage at 3°C was shown to be effective in preserving quality, while 'Shine Muscat' exhibited greater resistance to deterioration than 'Flame Seedless'. Handheld colorimeters provide a promising tool for simplified quality control; this study demonstrates the potential of using fruit color parameters as reliable, non-invasive indicators for predicting postharvest weight loss and texture changes in table grapes. Using convolutional neural networks (CNNs), we developed predictive models with high accuracy, highlighting the feasibility of integrating image-based color analysis into postharvest monitoring systems. The results indicate that lower storage temperatures (such as 3°C) effectively reduce weight loss and maintain fruit texture, providing valuable insights for optimizing storage conditions. Furthermore, cultivar differences play a significant role in postharvest quality retention, with 'Shine Muscat' exhibiting lower weight loss and superior textural stability compared to 'Flame Seedless'. The results of this research highlight the importance of adopting advanced, technology-driven approaches to postharvest quality assessment. Implementing machine learning-based colorimetric analysis offers a scalable and efficient solution for fruit storage management, reducing losses and ensuring product quality. Future research should focus on refining predictive models by incorporating additional quality indicators and expanding the dataset to enhance model generalizability across a wide range of grape varieties and storage conditions. By further integrating artificial intelligence into postharvest management, the fruit industry can move towards more data-driven, efficient, and sustainable quality control practices.

Ethical statement

The research presented doesn't involve any animal or human study.

CRediT authorship contribution statement

Xiaoyan Cheng: Writing – review & editing, Writing – original draft, Funding acquisition. **Yao Zhou:** Data curation. **Zhengyang Huo:** Formal analysis. **Ruiying Li:** Investigation. **Shiqian Xu:** Software. **Hao Qi:** Software. **Jianyuan Zhu:** Methodology. **Fei Wang:** Resources. **Yang Bi:** Visualization, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no competing interests.

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Data availability

Data will be made available on request.

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