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HYPERSPECTRAL METHOD INTEGRATED WITH MACHINE LEARNING TO PREDICT THE ACIDITY AND SOLUBLE SOLID CONTENT VALUES OF KIWI FRUIT DURING THE STORAGE PERIOD

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Non-destructive evaluation is advancing in examining the properties of fruits. Kiwi fruit stands out as one of the popular fruits globally. Due to the influence of various environmental factors and storage conditions, diligent checking and storage of this fruit are essential. Therefore, monitoring changes in its properties during storage in cold storage facilities is crucial. One non-destructive method utilised in recent years to investigate changes in fruit texture is the hyperspectral method. This study uses the support vector machine (SVM) method to assess hyperspectral method's effectiveness in examining property changes in four kiwi varieties during storage in addition to predicting the properties such as acidity and soluble solid content. The evaluation of the predictive machine learning model revealed an accuracy of 95% in predicting acidity and soluble solid content (SSC) changes in kiwi fruit during storage. Further, investigations found that the support vector machine method provided relatively lower accuracy and sensitivity in identifying product variety during storage, with an average accuracy ranging from about 91% to 94%. These findings suggest that integrating machine learning methods with outputs from techniques like hyperspectral imaging enhances the non-destructive detection capability of fruits. This integration transforms obtained results into practical outcomes, serving as an interface between software and hardware.

Keywords: smart agriculture; fruit storage; machine learning; hyperspectral imaging; artificial intelligence; big data; data science; soft computing; sustainable development goals; quality control

After harvesting, kiwi fruit is stored in local cold storage facilities due to various pre-harvest effects such as cultivar selection and environmental conditions. These factors cause changes in fruit quality at harvest and during storage, which makes it challenging to categorise them based on their suitability for storage (Li et al., 2022). Fruit classification typically relies on destructively measured parameters related to ripeness, such as acidity and soluble solid content (SSC). Therefore, a thorough examination of these parameters is necessary for accurate fruit classification. However, since these assessments are typically destructive, they can only be performed on some products. Hence, a robust management strategy is essential to ensure quality throughout the agricultural and horticultural supply chain. Today, non-destructive detection methods have emerged as a robust strategy for estimating the quality of agricultural and horticultural products (Geyer et al., 2007; Wang et al., 2015; Li et al., 2018). One such method is spectroscopy, employed as a non-destructive means to assess the quality of agricultural and horticultural products (Chelpiński et al., 2019; Lazim et al., 2022; Ke et al., 2023). A promising approach involves using electromagnetic radiation, particularly visible/near-

infrared (Vis-NIR) spectroscopy (Assaad, 2020). Due to its accuracy and reproducibility, this advanced technology has gained considerable attention and demonstrates significant potential for enhancing postharvest methods in the fruit industry. On the other hand, the integration of this method with machine learning techniques can open new avenues for modelling and providing effective indices in conjunction with developing detectors and sensors. These models can develop more accurate and reliable forecasting and modelling packages than other models (Taghinezhad et al., 2023). Several studies have been conducted in this field to determine the properties and quality of kiwi fruit using this method. Table 1 presents some notable studies with details regarding the type of product, the type of spectroscopy, and its range. The studies presented in this table are sourced from the Scopus database.

According to the information presented in Table 1, the studies conducted on kiwi primarily focus on predicting product properties and handling, such as firmness and SSC. However, based on our studies, relatively few articles address product's acidity. Another category involves investigating the impact of kiwi fruit storage on product properties and

Table 1 A list of significant studies in the detection of properties and quality of Kiwi by spectrometry

References	Model	Dependent variables	Type	Range (nm)	Product
Ke et al. (2023)	CNN	hardness	hyperspectral imaging	400–1000	kiwi fruit
Ebrahimi et al. (2023)	CNN	ripeness	hyperspectral imaging	N.A.	kiwi fruit
Reis-Pereira et al. (2022)	SVM	kiwi plant canker diagnosis	hyperspectral U.V.–VIS	325–1075	kiwi fruit
Benelli et al. (2022)	PLS	SSC and hardness	hyperspectral imaging	400–1000	kiwi fruit
Sarkar et al. (2020)	PLS and SVM	SSC	Vis/NIR	730–970	kiwi fruit
Niu et al. (2018)	SVM	<i>Zygosacchomyces rouxii</i>	NIR	800–2450	kiwi fruit
Lue et al. (2010)	GA-PLS	dry matter	NIR	400–2500	kiwi fruit

quality, which has received less attention in literature. The primary innovation of this study lies in integrating the hyperspectral (Vis-NIR) method with machine learning techniques to develop a model for predicting the properties of kiwi fruit across four different varieties during storage. This study comprises four fundamental steps. The first step involves preparing various types of kiwi and collecting data at different storage intervals. The subsequent step is to analyse spectral data and identify effective wavelengths. Following this, modelling is conducted using machine learning methods, and finally, the results are extracted along with appropriate recommendations.

Material and methods

This study selected four varieties of kiwi fruit, including Alison, Golden, Hayward, and Red, as tested samples. Kiwi fruit is a globally commercialised fruit from the Actinidiaceae family, rich in nutrients like vitamins, minerals, and phytochemicals and known for its medicinal benefits, helping with cardiovascular diseases, diabetes, kidney issues, cancer, digestive disorders, and bone and eye problems (Satpal et al., 2021). These products were subjected to physical and chemical properties tests during different

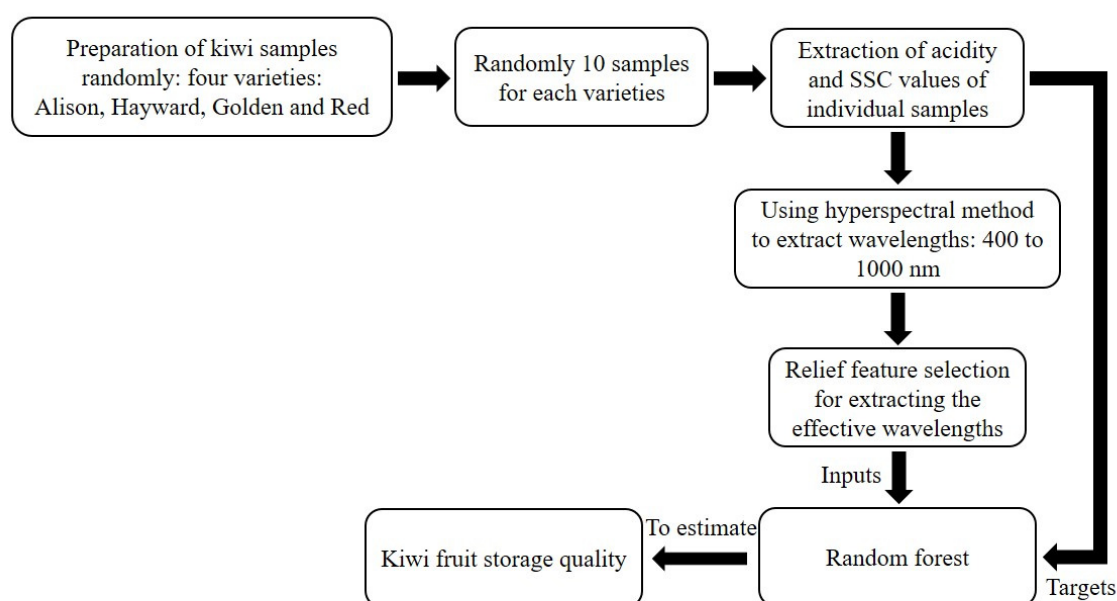
storage periods, followed by hyperspectral photography. The obtained properties and effective spectra were selected as dependent and independent variables and subjected to modelling with the machine learning method. The details of each test step are discussed in the following (Fig. 1).

Feature selection

In this section, four different varieties, including Alison, Golden, Hayward, and Red, and ten samples from each were selected as samples under test. In the continuation of these samples, they were placed under the conditions of kiwi storage (temperature of about 4 °C, which was chosen in consultation with experts in this field). The time interval of data collection was considered to be seven days, and these seven days were chosen on average by forming a focus group and consulting with this group. The next step presents how to collect data with a hyperspectral camera.

Hyperspectral imaging

Figure 2 depicts the hyperspectral imaging setup, which comprises a custom-designed light-insulated enclosure which houses an image sensor, a charge-coupled device (CCD) camera, a light source, and the sample under examination. Additionally, a computer situated externally to the enclosure, supported by an information and

**Fig. 1** Research procedure flowchart

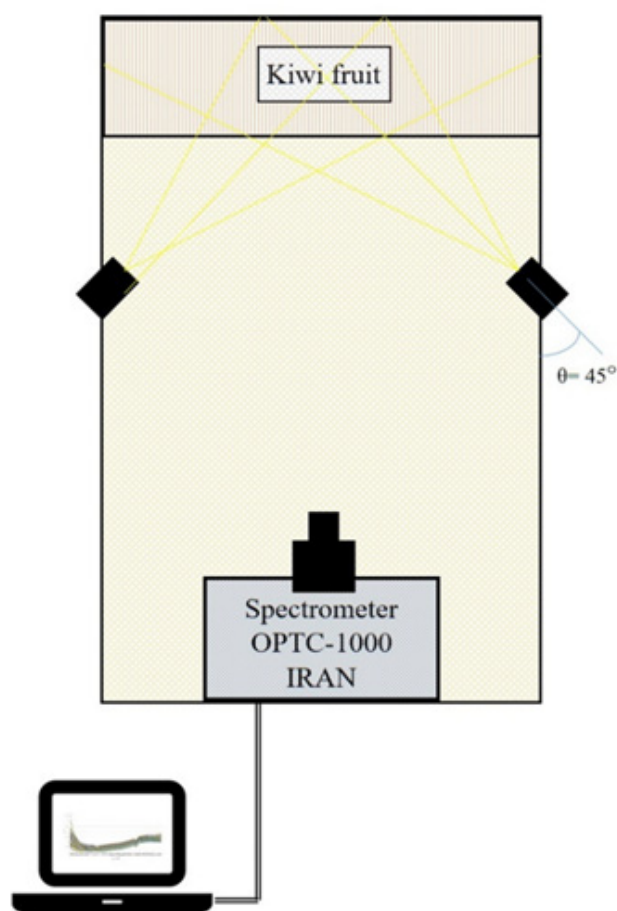


Fig. 2 Hyperspectral imaging setup

control system (Spectrometer OPTC-1000, Iran), facilitates data processing. The line scan camera within the system captures images spanning up to 720 × 440 mm, achieving a resolution of 0.2 mm within a timeframe of 10 to 110 ms. Operating within the spectral range of 190 to 1150 nm with 1 nm resolution, the camera emphasises 400 and 1000 nm wavelengths to ensure stable imaging by mitigating noise interference.

Hyperspectral imaging was performed in the Laboratory for Measuring Physical and Chemical Properties of Agricultural Products at the Faculty of Agricultural and Natural Sciences of the University Mohaghegh Ardabili. Each sample was subjected to 350 scans for 300 ms,

which recorded 1279 wavelengths in each hyperspectral reflectance image. After imaging, 40 kernels were randomly selected and weighed using a digital scale. Although the images present good quality for future research, using image denoising is suggested by e.g., Onur (2022).

Measuring kiwi fruit properties

Table 2 presents a statistical summary of the physicochemical properties (measured) of kiwi samples, including acidity and SSC. The statistical analysis was conducted using mean test with SPSS software.

A laboratory digital scale with an accuracy of 0.1 g was used to measure weight. A spectrophotometer was used to detect SSC. In this method, the juice of the product was first extracted. Then, the obtained water values were measured using a dropper in the spectrophotometer (Optizen 2120 UVplus). An acidity measuring device with an accuracy of 0.01 was used to continue measuring the pH values.

Feature selection for extracting effective wavelengths

The relief feature selection method, a widespread machine learning and data mining technique, was used to identify effective wavelengths. This method evaluates the relevance of each feature by analysing their impact on classification accuracy (Rosario and Thangadurai, 2015; Urbanowicz et al., 2018). It calculates relief scores based on the difference in feature values between nearby samples in the feature space. Features that show significant differences are given higher scores, especially those that show variation among the samples of different classes, indicating their importance in classification (Rosario and Thangadurai, 2015; Urbanowicz et al., 2018). To implement this algorithm, the characteristics of the experimental test were selected as dependent variables, while the wavelengths served as independent variables in MATLAB 2021 software. This process assigned scores to wavelengths; five were identified as influential independent variables.

Modelling

The model was developed using the support vector machine (SVM) method to predict the product characteristics during the storage period. The theoretical explanation of this model is presented by Suthaharan (2016). In this model, the effective wavelengths selected based on the length of the storage period were selected as model inputs, and acidity and SSC were selected as model outputs. In this

Table 2 Statistical analysis of kiwi fruit properties

Property	Variety	Unit	Minimum	Maximum	Mean	Standard deviation
pH	Alison	–	3.05	3.61	3.33	0.22
	Hayward		3.16	4.39	3.71	0.47
	Golden		3.13	3.78	3.34	0.21
	Red		3.63	4.85	4.14	0.42
SSC	Alison	Brix	11.6	14.9	12.84	1.13
	Hayward		4.9	12.4	8.96	3.32
	Golden		10.5	13.2	11.7	0.98
	Alison		17.9	22.7	18.96	1.87

model, 75% of the data were randomly classified as network training data and 25% as network test data. Python 3.8 software with Scikit-Learn (V 1.1) library was used to model in a computer Intel(R) Core (T.M.) i7-8550U CPU with a frequency of 1.80 GHz and a RAM memory of 32 GB.

Two statistical indicators, the correlation coefficient and the root mean square error (according to Eqs 1 and 2), were used to evaluate the model.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \hat{x}_i)^2} \quad (1)$$

$$CC = \frac{Cov(x, \hat{x})}{\sigma_x \sigma_{\hat{x}}} \quad (2)$$

where: $\hat{x}$ – refers to the predicted values; x – refers to the target values; N – refers to the number of samples

Results and discussion

This part of the study presents the results categorised into two

general parts. The first part presents the spectroscopic graphs, and the second presents the modelling results.

Figure 3 shows the output graphs from hyperspectral imaging in two scenarios. The first scenario (Fig. 3a) separates the samples according to variety (in four treatments, including Alison, Golden, Hayward, and Red), and the second diagram (Fig. 3b) separates the samples according to time. Storage is separated into five treatments (first to fifth week). As is clear, the difference between the treatments is evident in both scenarios, so this difference increases in the approximate range of 450–740 nm.

As it is clear from Fig. 3, the output of the feature selection method (with the relief method) is also shown separately for dependent variables (including SSC and pH) in each scenario. Based on what is clear from Fig. 3a, in the scenario of separation by species, wavelengths 693, 710, 725, 745, and 759 about SSC have obtained the highest score from the feature selection method, and wavelengths 654, 700, 715, 724, and 737 have

obtained the highest score about pH. This shows that in the classification according to species, the wavelengths are located in the approximate infrared range. One of the reasons for this is the unique molecular properties of kiwi fruit in the infrared range. Infrared spectroscopy allows the measurement of chemical composition by analysing the vibration and rotation of molecules, making it ideal for quantifying acidity and SSC levels in kiwi fruit. The infrared spectrum provides detailed information on the linkages and functional groups present in the fruit components, which allows accurate differentiation among species based on their acidity and SSC profile, essential for the quality control and market classification of kiwi fruit.

According to Fig. 3b, it can be seen that when the scenario moves towards the product classification according to the storage time, about the SSC parameter, wavelengths 759, 762, 763, 765, and 769 are effective wavelengths which are in the infrared range. This is almost similar to the scenario related to the classification according to the type of variety for the kiwi product. However, concerning the pH parameter, wavelengths 442, 444, 445, 446, and 449 are selected as effective wavelengths in the visible spectra range. According to the study by Reis-Pereira et al. (2022), effective reflectance values were observed for the blue region (450–520 nm) and most NIR regions (850–1075 nm) with an accuracy of 0.85. In the study by Sarkar et al. (2020), wavelength region (729–975 nm) was proposed for the analysis of carbohydrate, sugar, and water absorbance bands in the NIR region. One of the reasons is that the increase in storage time affects the ripeness of the kiwi product. Accordingly, as kiwi fruit ripens, its acidity level usually decreases, accompanied by changes in colour intensity, especially in the visible spectrum range. Visible spectra capture these colour changes caused by changes in the concentration of pigments such as chlorophyll, carotenoids, and anthocyanins, which indicate fruit ripening and shelf life. Therefore, the analysis of visible spectra allows accurate determination of acidity levels as a proxy for storage

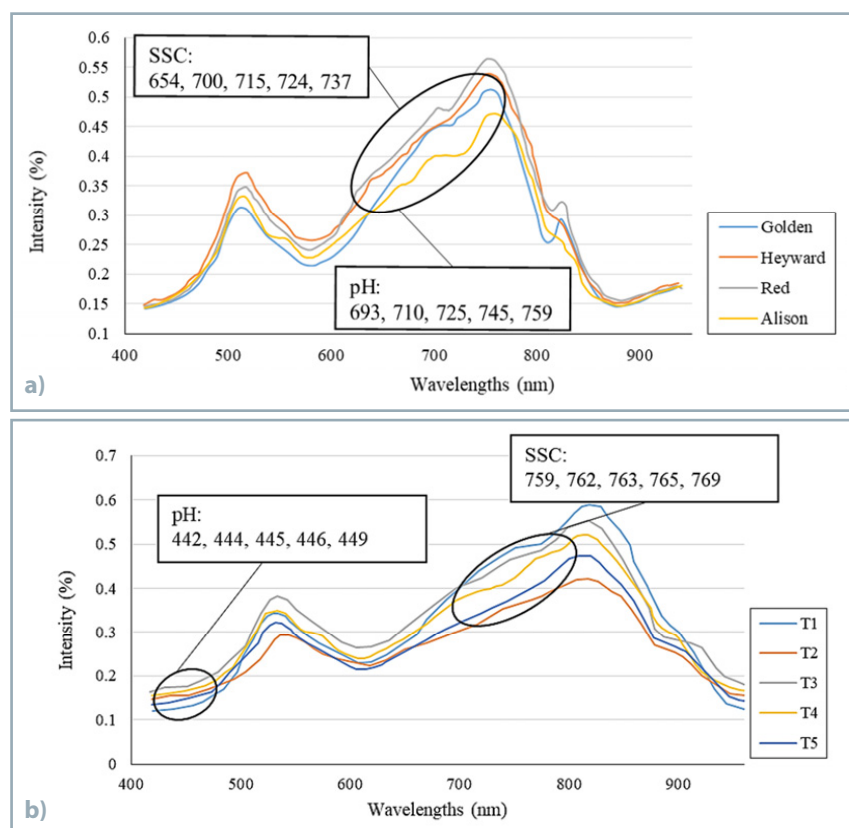


Fig. 3 Hyperspectral imaging output graphs
a) According to the type of variety; b) According to the storage time

Table 3 The results of the network training phase

Scenario	Property	RMSE	CC
Storage	pH	0.105	0.95
	SSC (unit: Brix)	1.12	0.96
Variety	pH	0.121	0.94
	SSC (unit: Brix)	1.38	0.91

time in kiwi fruit and facilitates optimal timing for harvesting and storage management practices.

Modelling results

This part of the study presents the results of modelling to identify the type of variety and the storage time of kiwi fruit according to the wavelengths affecting the dependent variables (i.e., pH and SSC). Table 3 presents network training

results in two scenarios: kiwi product storage and product variety detection. Table 3 evaluated the selected network (including kernel-type polynomial with $g = 0.08$, $c = 0.04$, and $d = 12$) with root mean square error (RMSE) and correlation coefficient (CC) parameters. Based on this, in predicting pH, the presented network for detecting storage has performed relatively better than detecting the type of variety (with a correlation coefficient of 0.95 and a root mean square

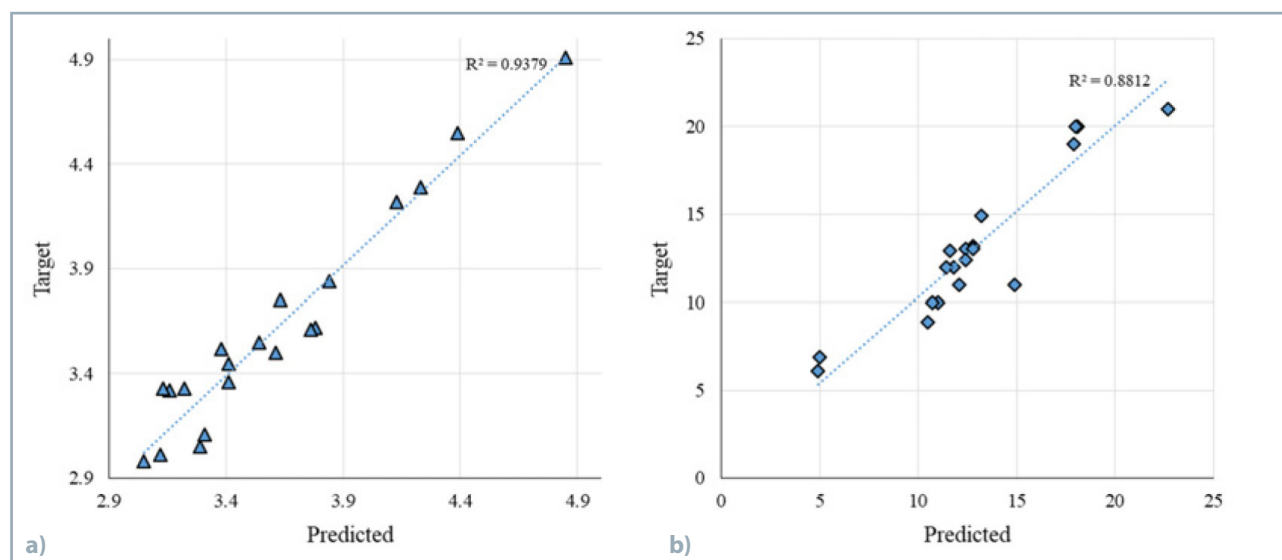


Fig. 4 Diagrams of the testing phase in identifying the type of kiwi fruit variety
a) pH; b) SSC (unit: Brix)

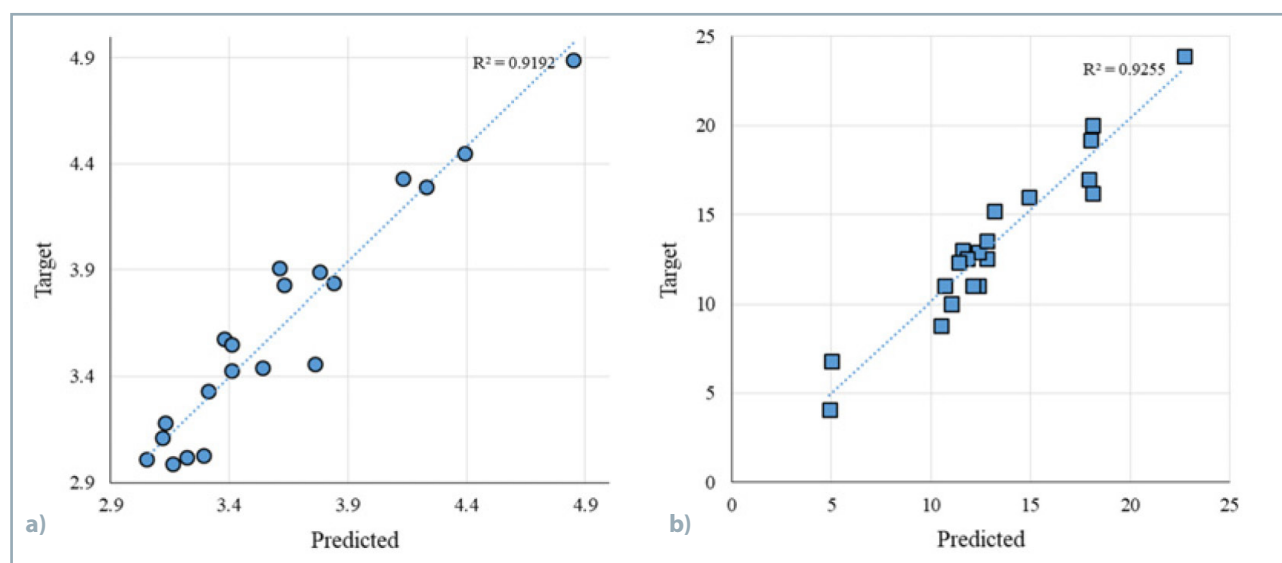


Fig. 5 Diagrams of the testing phase in identifying kiwi fruit storage
a) pH; b) SSC (unit: Brix)

error of 0.105). This process has a more noticeable difference in SSC prediction, so the accuracy of SSC prediction in storage detection has improved by about 5.5% compared to variety-type detection.

In the study by Benelli et al. (2022), the ripeness evaluation of kiwi fruit was conducted by hyperspectral imaging at 400–1000 nm (Vis/NIR). Partial least square integrated with discriminant analysis provided a correlation coefficient of 0.85 for the classification of samples. In the study by Ebrahimi et al. (2023), convolutional neural networks provided a correlation coefficient of about 0.91 for the bruise detection in kiwi fruit. According to the previous studies, the results of the present study provide more effective and reliable results for the prediction of varieties and storage time because the present study employed the effective wavelengths extracted by relief feature selection score and eliminated the less effective inputs in the modelling procedure which can be one of the important solutions. Based on this, this network was used as the selected network in the test phase with the test phase data. Figures 4 and 5, respectively, show the results of the testing step of SVM for variety detection and storage time detection in the form of plot diagrams. As it is known, the accuracy in detecting storage time in terms of effective wavelengths is, on average, 2–5% better than detecting the type of variety.

As mentioned, hyperspectral imaging detects kiwi fruit storage time with higher accuracy than species classification because it can capture a wide range of spectral information, including subtle changes in colour, texture, and chemical composition. While species classification mainly focuses on genetic differences between kiwi fruit cultivars, which may not always be directly related to storage time changes, hyperspectral imaging considers the dynamic changes in fruit characteristics during storage. These changes, such as changes in pigmentation, texture, and biochemical composition, are better captured by hyperspectral imaging and allow for more accurate identification of fruits based on their storage duration. In conclusion, hyperspectral imaging provides a more comprehensive approach to fruit quality and ripening assessment, leading to higher accuracy in determining storage time than species classification alone.

Conclusion

Based on the results obtained, to integrate hyperspectral imaging with machine learning techniques proved to be an effective method to predict the acidity and SSC of kiwi fruit during storage. By using the hyperspectral data and the robust analytical capabilities of machine learning algorithms, this approach provided a comprehensive, non-destructive tool for monitoring fruit quality over time. It demonstrated potential to enhance postharvest management practices and ensure product quality and market competitiveness by predicting the acidity and pH levels which are the key indicators of kiwi fruit ripening and shelf life. The non-destructive nature of this method makes it an attractive option for the fruit industry, to enable real-time evaluation and decision-making to optimise storage conditions and reduce postharvest losses. Future directions include refining and developing advanced algorithms, such as deep learning techniques, to enhance prediction

accuracy and efficiency. Integrating this technology with IoT can enable real-time, remote monitoring and smart storage systems that autonomously adjust conditions. Expanding applications to other fruits and agricultural products, assessing additional quality parameters, reducing costs to make the technology accessible to SMEs, and developing portable, user-friendly devices are also essential. Establishing standardised protocols and conducting validation studies will support regulatory acceptance and adoption, improving overall food quality, safety, and sustainability.

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