

Article

Vis/NIR-Based Wireless Sensing for Potatoes

Chunling Liu ^{1,†}, Ruihua Zhang ^{1,†}, Wenjing Zhao ¹, Yuhang Gong ¹, Yingle Du ¹, Tao Sun ², Wei Liu ³ and Xinqing Xiao ^{1,*}

¹ College of Engineering, China Agricultural University, Beijing 100083, China

² Institute of Agricultural Quality Standards and Testing Technology, Xinjiang Academy of Agricultural Sciences, Urumqi 830091, China

³ Ulanqab Product Quality Measurement Inspection and Testing Center, Ulanqab 012001, China

* Correspondence: xxqjd@cau.edu.cn

† These authors contributed equally to this work.

Abstract

Potato quality is determined by multiple physicochemical indicators, including dry matter content (DC), starch content (SC), and color parameters (lightness L^* , redness a^* , yellowness b^* , and browning index (BI)). Conventional spectrometers are costly, non-portable and lack wireless in-situ monitoring, restricting efficient postharvest quality assessment. Chemical methods are destructive and inefficient for field inspection and high-throughput detection. The primary objective of this study was to develop and validate a low-cost wireless 12-channel visible/near-infrared (Vis/NIR) spectral sensing system, comprising 6 Vis channels and 6 NIR channels, for the real-time non-destructive prediction of six potato quality indicators. After preprocessing the spectral data with mean normalization, a multiple linear regression (MLR) model was established to optimize the prediction performance of quality parameters. The six indicators evaluated were DC, SC, L^* , a^* , b^* , and BI. Statistical analysis and cross-validation were further conducted to quantitatively evaluate the stability and credibility of the prediction model. Among these, the b^* parameter demonstrated the most robust predictive performance, achieving a cross-validated coefficient of determination (R^2_{cv}) of 0.881. The MLR model was integrated into the sensing hardware to realize synchronous data collection and prediction. This study provides a validated, low-cost, wireless solution for rapid potato quality assessment under controlled conditions, offering a potential alternative to conventional spectrometers and destructive chemical methods.

Keywords: Vis/NIR spectroscopy; wireless sensing; quality prediction; non-destructive detection; MLR model

Academic Editor: Mikael Sjö Dahl

Received: 7 July 2026

Revised: 1 August 2026

Accepted: 4 August 2026

Published: 5 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The vegetable industry plays an important role in the global agricultural economy, and vegetable quality is a key determinant of its economic value [1,2]. Postharvest vegetables undergo continuous respiration, transpiration, and redox reactions, leading to irreversible quality loss [2–4]. Traditional quality detection mainly relies on manual judgment, which is inefficient and subjective, leading to unreliable results [2,5,6]. Conventional chemical methods rely on destructive sampling [5–7]. Consequently, conventional detection approaches have notable limitations in large-scale and high-throughput applications, and fail to meet the requirements of modern intelligent agriculture. Efficient, low-

cost and non-destructive testing technologies are urgently needed to improve postharvest quality assessment and monitoring. This study developed a low-cost, portable, wireless spectral sensing system to overcome the limitations of traditional detection methods.

Vis/NIR spectroscopy has become a primary technique for potato quality evaluation due to its rapidity, non-invasiveness, and efficiency [8–12]. Although progress has been achieved in predicting DC, SC, soluble solids, biochemical components, and physiological indicators of potatoes using conventional benchtop and portable NIR systems [8–13], most existing studies rely on either bulky benchtop spectrometers or handheld portable devices, both of which present notable limitations for practical postharvest applications. Benchtop spectrometers offer satisfactory precision but are bulky, costly, and non-portable, making field deployment and dynamic monitoring infeasible [11–13]. Portable NIR devices support on-site detection, yet they still necessitate manual close-range operation, thus failing to realize long-term, real-time, or unattended monitoring [11–13]. Furthermore, the vast majority of current research prioritizes laboratory-based model development using high-performance instruments, with limited attention to engineering practicability, low-cost hardware integration, and adaptability to unstructured field environments [8–10,13]. These limitations hinder the practical extension of spectral detection in the potato postharvest industry. A low-cost 12-channel spectral sensing system based on AS7262 and AS7263 was developed to reduce the equipment cost associated with conventional spectrometers. Wireless transmission and cloud access were integrated to realize on-site real-time monitoring and improve the flexibility of field measurement. Mean normalization and a lightweight MLR model were adopted to match the embedded hardware and support potential future on-site applications.

Accordingly, to address the abovementioned limitations of existing Vis/NIR detection technologies for potato postharvest quality management, the present study aimed to develop a portable, wireless, low-cost 12-channel Vis/NIR optical sensing system for rapid and non-destructive quality assessment of potatoes under temperature-stable postharvest conditions, as a preliminary step toward future deployment in storage and transportation scenarios. Specifically, we collected Vis/NIR spectral data from two commercial potato cultivars, preprocessed the data using mean normalization consistent with the pre-optimized scheme above, and constructed an MLR prediction model for six core potato quality indicators, namely DC, SC, L^* , a^* , b^* , and BI. The optimized MLR model was integrated into the developed sensing hardware to achieve synchronous spectral data acquisition, wireless transmission and on-site real-time prediction. The performance and reliability of the system were validated using potato samples under controlled laboratory conditions, confirming its capability for non-destructive quality assessment. The system integrates low-cost hardware design, wireless real-time monitoring, and embedded lightweight modelling for potato quality assessment. It serves as a proof-of-concept demonstration that an ultra-low-cost chip-scale multispectral sensor can provide useful predictive information for potato quality screening, and may help advance the transition from laboratory spectral research to on-site agricultural applications.

2. Materials and Methods

2.1. Sample Acquisition and Pretreatment

In this study, two potato varieties, namely Dutch No.15 and Atlantic, with uniform commercial maturity, were selected as experimental materials. These two varieties were sourced from different production regions, which introduced additional variability in growth conditions, peel properties and tuber phenotypic traits. All samples were purchased from a professional agricultural product wholesale platform. Upon arrival at the laboratory, the samples were immediately placed in a low-temperature incubator for pretreatment. The incubator had a temperature control accuracy of plus or minus 0.5 degrees

Celsius, with a constant set temperature of 3 degrees Celsius. This measure was intended to eliminate potential interference from temperature fluctuations during transportation on the experimental results [14]. The samples were divided into two independent experimental groups according to variety. Before formal experiments, intact potatoes free from mechanical damage and pathological defects were selected. The potato surfaces were cleaned with deionized water, wiped dry, and equilibrated at room temperature (25 ± 1 °C) for 30 min to eliminate the influence of temperature differences. Prior to spectral collection, all potato tubers were visually inspected to exclude samples with severe mechanical damage or pathological defects. Although samples with evidently unusual peel thickness or pigmentation were not deliberately selected, we acknowledge that natural variations in peel properties across different cultivars and individual tubers were not systematically controlled or quantified in this study. A total of 160 qualified potato samples were finally prepared for formal analysis, including 80 for Dutch No.15 and 80 for Atlantic, and all samples were subjected to spectral data acquisition and physicochemical reference index measurement.

2.2. Acquisition of Sample Spectral Data

All spectral measurements were performed at a controlled ambient temperature of 25 ± 1 °C to ensure consistency across all samples. The spectral sensing module employs the AS7262 Vis sensor (450 nm–650 nm) and AS7263 NIR sensor (610–860 nm) from ams OSRAM AG, Premstaetten, Austria. The AS7262 and AS7263 sensors are commercially available multispectral devices. Lopin et al. [15] systematically assessed the performance of these sensors for plant biochemical detection tasks and demonstrated that discrete-wavelength sensors of this type can achieve prediction accuracy comparable to full-spectrum instruments for targets with distinct characteristic absorption bands [15]. The sensors integrate a controllable LED driver to provide the measurement light source, and a built-in microcontroller that processes raw data and outputs adjusted values via an I²C interface. During the data acquisition process, the radiant light emitted by the light source penetrates the potato epidermis and produces a diffuse reflection phenomenon, which is received by the Vis/NIR sensor, and the reflected spectral signals are recorded. For each sample, spectral data were collected from three representative regions of the tuber, namely the apical, middle, and basal parts. Each position was measured in triplicate, and the average of nine determinations was used as the final spectral data to ensure data repeatability and stability.

2.3. Acquisition of Physical and Chemical Indicators of Samples

After acquiring the Vis/NIR spectral data, the potato tubers were numbered in sequence and subjected to physicochemical analysis, including the measurement of CIELAB color space parameters (L^* , a^* , b^*), DC determination, and SC determination. Color data were collected three times from three representative regions of the tuber, namely the top, middle, and bottom. The arithmetic mean of all measured data was used as the characteristic value of this sample.

The average value of these three measurements was selected as the color value of the sample, and BI was calculated based on the average values of L^* , a^* , and b^* [16].

The calculation formula for BI is given in Equation (1).

$$BI = \frac{100 \times (x - 0.31)}{0.172 + 1.75x} = \frac{5.645 \times L^* - 3.012 \times b^*}{L^* + a^* + b^*} \quad (1)$$

Then, the potatoes were peeled and cut into pieces. Centering on the spectral acquisition area, they were cut into small pieces of uniform thickness. A 10–20 g sample was randomly selected and placed in a 7 cm diameter circular glass petri dish. With the help

of an analytical balance with an accuracy of 0.1 mg, the weight of the aluminum box and the sample to be tested was measured to obtain the weight G_1 . Subsequently, the sample was placed in a constant-temperature drying oven for drying treatment, with the drying temperature set to 90 °C. When the sample and the aluminum box reached a constant weight state, they were weighed to obtain the weight G_2 . After the sample was taken out, the aluminum box was weighed separately to obtain the weight G_3 . Then, the DC of the potato was calculated using the formula. Each sample was determined three times, and the average value was taken as the DC of this sample.

The calculation formula for DC is given in Equation (2).

$$\omega = \frac{G_2 - G_3}{G_1 - G_3} \times 100\% \quad (2)$$

The determination of starch content was performed with reference to the iodine colorimetric method. The principle is that starch in the sample to be tested can be extracted using an ethanol solution and an 80% calcium nitrate ($\text{Ca}(\text{NO}_3)_2$) solution. Starch reacts with iodine-potassium iodide solution under acidic conditions to produce a colored complex. The absorbance of the colored solution at 600 nm was measured using an ultraviolet-visible (UV-Vis) spectrophotometer, and the starch content in the sample was calculated based on the absorbance value. Each sample was assayed in triplicate, and the average value was taken as the starch content of the sample.

2.4. Spectral Data Processing and Model Construction Method

To construct accurate prediction models for potato quality indicators, four preprocessing methods were applied to the raw spectral data, namely mean normalization (norm), standard normal variate transformation (SNV), SNV followed by mean normalization (SNV-norm), and multiplicative scatter correction followed by mean normalization (MSC-norm). On this basis, three types of prediction models, namely partial least squares regression (PLSR), support vector regression (SVM), and MLR, were established to realize the quantitative prediction of DC, SC, L^* , a^* , b^* , and BI. SNV and MSC are classical preprocessing methods for continuous full-range spectra. However, the proposed system collects only 12 discrete wavelengths, where spectral data are sparsely distributed and variation patterns differ from those in continuous spectra. Therefore, directly applying methods designed for continuous spectra may not be optimal for this sensor configuration, and a comparative evaluation of candidate methods was considered necessary. After systematic comparison, mean normalization was identified as the optimal strategy and adopted as the sole preprocessing approach for final model development. SVR modelling was performed using Unscrambler X10.4 with the RBF kernel function and default parameters ($C = 1$, $\varepsilon = 0.1$) as implemented in the software. All 160 potato samples were divided into a calibration set and a prediction set at a ratio of 3:1 using a stratified random sampling strategy. Specifically, the samples were first sorted by variety and spectral similarity into 8 groups of 20, then 5 samples were randomly drawn from each group to form the prediction set, with the remaining 15 from each group assigned to the calibration set. This ensured that both subsets covered the full range of spectral and quality variability. A fixed random seed was used to guarantee reproducibility. To verify the representativeness of the split, independent sample t -tests were conducted on all six quality indicators between the two subsets, and no significant differences were found ($p > 0.05$). The random split generated evenly distributed samples without significant bias. The calibration set was subjected to cross-validation to prevent model overfitting and improve the robustness and generalization ability [17]. To objectively and comprehensively evaluate model performance, a full set of statistical indicators was used. The coefficient of determination for calibration (R^2_c), R^2_{cv} , root mean square error of calibration (RMSEC), and root mean square error of cross-validation (RMSECV) were employed to quantify the fitting accuracy

and robustness of the model [18]. The coefficient of determination for prediction (R^2_p) and root mean square error of prediction (RMSEP) were applied to evaluate external prediction ability. The residual predictive deviation (RPD) was calculated as the ratio of the standard deviation (SD) of the measured values to RMSECV, which was adopted to evaluate the practical application potential of the model [19]. To provide a more comprehensive evaluation, several complementary diagnostic metrics were examined. Bias was calculated as the mean difference between predicted and measured values to identify systematic prediction errors. The slope and intercept of the regression between predicted and measured values were evaluated; a slope approaching 1 and an intercept approaching 0 indicate good agreement. RPD was interpreted using widely adopted classification thresholds. Residual plots were inspected to detect heteroscedasticity and systematic distribution patterns. Collectively, these complementary metrics enable a more rigorous assessment of model performance rather than relying solely on R^2 .

3. Results and Discussion

To overcome the destructive, offline, non-portable and lack of wireless in-situ monitoring limitations of traditional potato quality detection, this study developed a low-cost, wireless 12-channel Vis/NIR spectral sensing system for real-time, non-destructive quality assessment, with potential for future application in postharvest scenarios. As shown in Figure 1a, the 12-channel Vis/NIR spectral sensing system integrates two 6-channel spectral sensors (AS7262 and AS7263) to acquire spectral signals at discrete wavelengths of 450 nm, 500 nm, 550 nm, 570 nm, 600 nm, 610 nm, 650 nm, 680 nm, 730 nm, 760 nm, 810 nm, and 860 nm. The visible range of 450–680 nm covers characteristic absorption bands of tuber pigments (carotenoids, anthocyanins), enabling the prediction of potato color-related indicators including L^* , a^* , b^* and BI. The 730–860 nm near-infrared region corresponds to the third overtone absorption of C–H and O–H bonds, which are sensitive to internal carbohydrate and moisture contents relevant to DC and SC. These candidate sensitive bands were preliminarily screened by referring to published Vis/NIR studies on potato quality detection. Wavelengths carrying highly overlapping spectral information were eliminated to reduce data redundancy. On the basis of these target spectral regions, commercially available multi-wavelength sensors were screened, and the AS7262 and AS7263 photodiode sensors were finally selected, as their factory-fixed channels well cover the predetermined bands. This hardware solution supports the development of a low-cost, miniaturized wireless sensing platform. Equipped with wireless transmission modules, the proposed system exhibits superior portability and wireless data transmission capability compared with bulky laboratory spectrometers and conventional handheld detection devices. Specifically, light emitted by the built-in LEDs irradiates the potato surface, and the integrated photodiode array captures diffuse reflected light and converts optical signals into electrical signals for subsequent analysis [20]. When light of a specific intensity irradiates the potato, photons primarily interact with the peel tissue before being detected as diffuse reflectance. Given that visible radiation penetrates only 1–2 mm and near-infrared radiation up to 860 nm is still partially attenuated by the dense peel layer, the measured spectral signals predominantly carry information from the peel surface rather than directly from the internal parenchyma where starch and dry matter are concentrated. Nevertheless, these peel-mediated spectral variations can still establish correlative relationships with internal quality attributes through chemometric modeling [8,21]. The multispectral sensor converts voltage/current signals into digital signals for output via the analog-to-digital converter (ADC) and digital-to-analog converter (DAC) modules. The ESP32, serving as a microcontroller unit (MCU), performs data communication with visible light sensors and near-infrared sensors on the I²C channel. The received spectral data information is transmitted to the cloud database via the Wi-Fi wireless

transmission module for storage and analysis. The system realizes synchronous spectral collection, wireless data transmission and real-time quality prediction. The developed platform shows promise for future deployment in potato postharvest storage, transportation and sales.

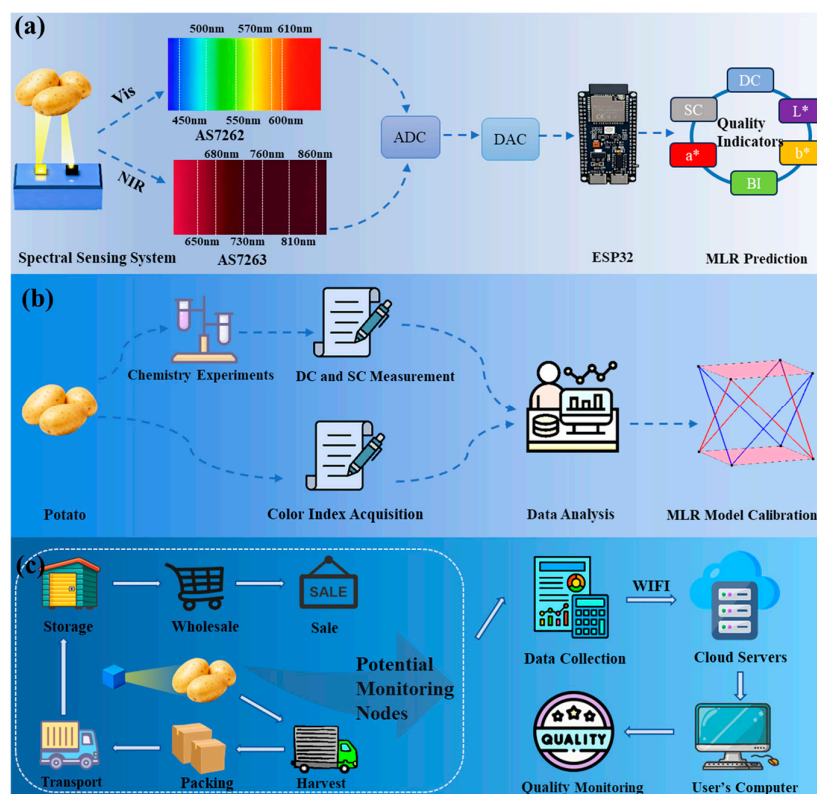


Figure 1. Schematic illustration of the potato quality evaluation approach based on spectral sensing and chemometric regression methods. (a) Validated data acquisition and MLR quantitative prediction pipeline of the 12-channel Vis/NIR wireless sensing system covering six quality indicators of DC, SC, L*, a*, b* and BI; (b) Laboratory workflow integrating physicochemical measurement, color index acquisition and MLR model calibration; (c) Prospective application framework of the wireless sensing system in postharvest potato supply chain monitoring with cloud data transmission.

Figure 1b illustrates the laboratory workflow of MLR model calibration, including two parallel branches of physicochemical measurement for internal quality indicators and color index acquisition for appearance parameters. All measured data are subsequently aggregated for statistical analysis and model fitting, which leads to the final MLR model calibration as the output of this workflow. Independent-sample *t*-tests confirmed significant differences ($p < 0.01$) in all six quality indicators between the two tested potato varieties, providing a solid statistical basis for model training and generalization performance evaluation. DC is the total solid fraction remaining after complete moisture removal and serves as a direct indicator of potato quality, as postharvest respiration continuously degrades dry matter into soluble substances [22]. Starch accounts for 60–80% of potato dry matter and largely determines processing and edible quality [23]. Color parameters (L*, a*, b*) and BI are core visual quality metrics, reflecting internal metabolism, nutritional value, and processing suitability [24]; L* specifically indicates enzymatic browning degree [5], a* and b* relate to non-enzymatic browning products, and BI integrates these three parameters to assess overall browning tendency during processing and storage [25]. In summary, these quality indicators link visual phenotypes to intrinsic quality through a

multi-dimensional quantitative framework. Following the data analysis and calibration procedure shown in Figure 1b, combined with the developed wireless sensing system, they support rapid, non-destructive prediction and show promise for future deployment in on-site postharvest quality assessment.

This study first acquired the reference data of six core potato quality indicators (DC, SC, L^* , a^* , b^* , BI) using standard physicochemical methods, and synchronously collected Vis/NIR spectral data via the developed wireless sensing system. The optimized MLR prediction model was embedded into the sensing hardware to achieve real-time quality prediction. The system provides a low-cost, wireless platform for rapid potato quality assessment, demonstrating the potential of using discrete-wavelength sensors for this purpose. The platform shows promise for future adaptation to postharvest scenarios (Figure 1c). Overall, this low-cost, wireless system offers a promising approach for non-destructive quality detection, offering a pathway from laboratory spectral research toward potential industrial applications.

As shown in Figure 2a, the self-developed Vis/NIR sensing system was used to collect the spectral reflectance of potato samples in the discrete wavelength range of 450 nm to 860 nm. The collected spectral curves exhibited multiple absorption peaks. These peaks arise from the electronic transitions of characteristic functional groups, which reflect the intrinsic compositional information of potatoes and are statistically correlated with the quality indicators investigated in this study [26,27]. For instance, the absorption peak around 650 nm is associated with chlorophyll [28], while the peak near 680 nm is related to chlorophyll a [29]. These peaks can indicate whether potatoes exhibit greening and correlate with color indicators related to L^* , a^* , and b^* . The peak at 730 nm is associated with the absorption of carotenoids, which can reflect the carotenoid content in potatoes [30]. These data are also closely correlated with color indices such as a^* and b^* . The spectral characteristics around 810 nm and 860 nm are related to the third overtones of O-H and C-H bonds [31] and are correlated with DC and SC. Notably, these third-overtone signatures are weak and prone to noise interference. The prominent absorption bands of starch and water derived from the second overtones of O-H and C-H are distributed in the 900–1400 nm short-wave infrared region, which is beyond the detection range of the adopted spectral sensors. Nevertheless, the 450–860 nm Vis-NIR range still contains distinguishable spectral information correlated with potato quality attributes. Indeed, previous studies have demonstrated that the 700–900 nm region can be effectively used for predicting dry matter and starch content in intact potatoes [11], and portable spectroscopic instruments utilizing discrete bands within the 700–1000 nm window are capable of achieving reliable non-destructive quantification of these two key indicators [12]. Combined with optimized spectral preprocessing and chemometric algorithms, effective quantitative prediction can be realized to meet the demand of preliminary postharvest quality monitoring. Spectral preprocessing can effectively reduce baseline drift, multiplicative scattering effect and environmental noise during spectral acquisition, retain the intrinsic spectral information related to potato chemical composition, and improve the signal-to-noise ratio and accuracy of subsequent prediction models [32]. In this study, four methods, namely norm (Figure 2b), SNV, SNV-norm, and MSC-norm (Figures S1–S3), were used to preprocess the spectra to screen the optimal preprocessing strategy and optimize the performance of subsequent potato quality prediction models. As shown in Figure 2b, normalization preprocessing enhanced the absorption features associated with chlorophyll, carotenoids, and carbohydrates. However, the other preprocessing methods were less effective at revealing these absorption features than mean normalization (Figures S1–S3). Mean normalization is beneficial for identifying and selecting effective wavelengths. This includes the 650 nm band for chlorophyll absorption [28], around 730 nm related to carotenoid absorption [30], and

the 810 nm and 860 nm bands corresponding to the third overtones of O–H and C–H bonds [31].

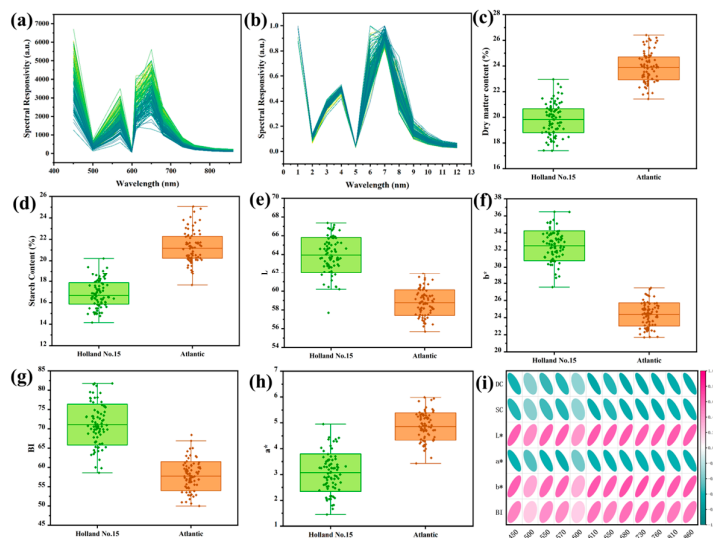


Figure 2. Spectral characteristics and comparative distribution of six quality indicators in potato samples. (a) Raw reflection spectra of all potato samples collected by the 12-channel spectral sensor; (b) Normalized reflection spectra of all potato samples collected by the 12-channel spectral sensor; (c) Comparative boxplot of DC; (d) Comparative boxplot of SC; (e) Comparative boxplot of L^* value; (f) Comparative boxplot of b^* value; (g) Comparative boxplot of BI value; (h) Comparative boxplot of a^* value; (i) Heatmap visualization of different potato indicators at a series of spectral wavelengths.

Figure 2c–h present the distribution differences of six key quality indicators between Dutch No.15 and Atlantic potato varieties using box plots with scatter points. The box plot intuitively presents the statistical central tendency and data dispersion range of each indicator, while the scatter points represent the measured values of individual samples. In terms of nutritional components (Figure 2c,d), Atlantic potatoes had a higher DC, mainly ranging from 23% to 25%, while that of Dutch No.15 potatoes was primarily concentrated between 19% and 21%. The SC of the two varieties showed the same trend as DC. The median SC of Atlantic potatoes was approximately 21%, while that of Dutch No.15 potatoes was around 17%. This characteristic indicates that Atlantic potatoes had higher DC accumulation efficiency and starch storage capacity, and exhibited superior nutrient accumulation characteristics. In terms of color characteristics, Dutch No.15 potatoes had significantly higher L^* and b^* values (Figure 2e,f), indicating a brighter appearance and a more pronounced yellow hue. In contrast, Atlantic potatoes had a higher a^* (Figure 2h), which may be related to the accumulation of pigment components such as anthocyanins in tubers [5,33]. Additionally, the Dutch No.15 potatoes had a significantly higher BI (Figure 2g), implying that this variety may have a higher browning tendency under equivalent processing or storage conditions [5,25,33]. The highly significant genotypic differences in all quality indicators between the two varieties provided a sufficient and reliable sample basis for the subsequent construction of universal quality prediction models.

To explore the statistical association between spectral signals and potato quality attributes, a correlation heatmap was constructed to visualize their pairwise correlation across the 450–860 nm Vis/NIR region (Figure 2i). The horizontal axis represents each spectral wavelength, and the vertical axis corresponds to the six measured quality indicators. The color gradient ranges from pink (positive correlation, correlation coefficient close

to 1) to green (negative correlation, correlation coefficient close to -1), which intuitively presents the magnitude and direction of the calculated correlation coefficients between quality indices and spectral bands. As illustrated in Figure 2i, different correlation patterns were observed among different indicators. DC, SC, and a^* values exhibited an overall negative correlation with most spectral wavelengths, and the correlation intensity varied with wavelength, with several bands exhibiting strong negative correlations. In contrast, L^* , b^* , and BI were predominantly positively correlated with spectral information, and the color gradient further revealed differences in positive correlation strength at different wavelengths. These significant correlations support effective variable selection and improve the interpretability of chemometric models for potato quality prediction. The strength of these correlations is conducive to variable selection and correlation analysis for establishing chemometrics-based models between potato quality indicators and spectral data. These results support the use of Vis/NIR spectroscopy for non-destructive quality evaluation of potatoes.

This study analyzed the original spectral data using four preprocessing methods, namely norm, SNV, SNV-norm, and MSC-norm. Three prediction models (PLSR, MLR, and SVM) were then constructed using the original and preprocessed spectra as input variables to predict six key potato quality indicators and identify the optimal combination of preprocessing method and prediction model. The results showed that the MLR model outperformed PLSR and SVM across all indicators (Figures 3a–i and S4a–i), with R^2_{cv} values ranging from 0.606 to 0.881. As shown in Figure 3a–i, the MLR consistently outperformed the PLSR and SVM across all preprocessing groups, with the lowest RMSECV, highest R^2_{cv} , and most reasonable RPD values (1.610–2.905). For DC, the MLR model achieved satisfactory predictive performance (Figure 3a–c and Table S1). Its R^2_{cv} ranged from 0.791 to 0.807, and its RPD ranged from 1.946 to 2.290, indicating acceptable predictive capability for screening purposes. For b^* , the MLR model achieved higher accuracy, with R^2_{cv} ranging from 0.829 to 0.881 and RPD values exceeding 2.0 for all preprocessing groups (Figure S4d–f), indicating good predictive performance. The MLR model showed limited predictive performance for BI, and its prediction accuracy ($R^2_{cv} = 0.726$) was the lowest among all quality indicators, as supported by Figure 3g–i and Table S6. This lower performance is likely due to overlapping spectral responses from endogenous metabolites and browning-related compounds in potato tubers. Nevertheless, MLR still outperformed PLSR and SVM for BI prediction.

The choice of preprocessing method also substantially influenced model performance, even when using the same spectral data and modelling algorithm. Among all preprocessing methods, mean normalization consistently yielded the best performance for the MLR model. As shown in Figure 3a–i and Tables S1–S6, mean normalization achieved the lowest RMSECV, highest R^2_{cv} , and highest RPD values, whereas SNV, SNV-norm, and MSC-norm resulted in varying degrees of performance degradation. The performance differences between preprocessing methods can be explained by the characteristics of the sensor configuration. SNV and MSC are established methods for correcting scattering effects in continuous full-range spectra. However, the proposed system operates at 12 discrete wavelengths, where spectral data are sparsely distributed. Under this condition, these methods tend to over-correct the spectral signals, eliminating subtle but quality-related variations and thereby reducing the sensitivity of subsequent models. In contrast, mean normalization adjusts spectral amplitudes without altering the relative spectral shape, making it more suitable for sparse wavelength data. This explains why mean normalization consistently outperformed the other methods in this study. For DC (Figure 3a–c and Table S1), all preprocessing methods except SNV improved prediction accuracy; mean normalization achieved the best performance with $R^2_{cv} = 0.798$, RMSECV = 0.0106, and RPD = 2.236. For the b^* value prediction model (Figure S4d–f and Table S5), the

combination of mean normalization preprocessing and the MLR model also exhibited the best predictive performance, with an R^2_{cv} of 0.881, an RMSECV of 1.432, and an RPD of 2.905. Notably, for mean normalization with MLR, the RPD values for DC, L^* , a^* , and b^* all exceeded 2.0 (Figures 3c and S4c,f,i), indicating acceptable predictive capability for screening applications. Overall, the MLR model with mean normalization consistently outperformed all other model-preprocessing combinations. The lower predictive performance of SVM, relative to both PLSR and MLR, can be attributed to three factors. Firstly, the correlations between potato quality indicators and Vis/NIR reflectance are predominantly linear. Applying nonlinear SVM to intrinsically linear modeling tasks introduces unnecessary overfitting risks and weakens generalization ability. Secondly, the self-developed sensing system only acquires 12 discrete wavelengths, resulting in a low-dimensional feature space that cannot fully activate the kernel-based nonlinear mapping advantage of SVM, whereas linear regression algorithms adapt better to sparse wavelength data. Thirdly, the calibration dataset contains approximately 120 samples. As a hyperparameter-sensitive nonlinear algorithm, SVM tends to deliver unstable predictions on small datasets; in contrast, MLR and PLSR exhibit stronger robustness without complicated hyperparameter tuning. Consistent with this trend, mean normalization with MLR yielded lower RMSECV, an R^2_{cv} closer to 1.0, and higher RPD values than other combinations. Unlike SVM and PLSR, MLR has low computational complexity and fast execution speed, making it suitable for real-time on-site monitoring on the system's embedded microcontroller. Therefore, mean normalization combined with MLR was selected as the preferred approach for non-destructive prediction of potato quality indicators in this system. Detailed numerical results, including RMSEC, R^2_c , RMSECV, R^2_{cv} , and RPD, for each model under different preprocessing methods, are provided in Tables S1–S6.

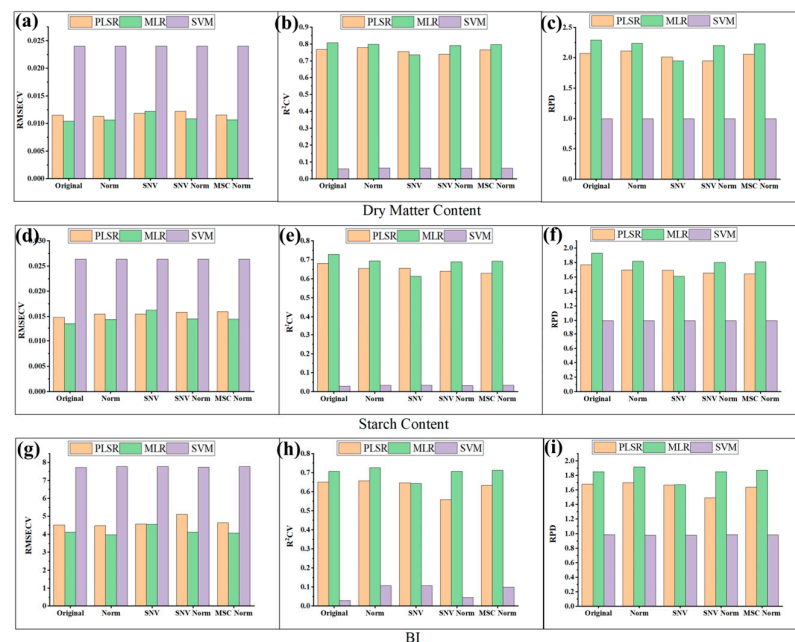


Figure 3. Visualization of the performance of potato quality indicator prediction models (PLSR, MLR, SVM) established using different preprocessing methods. (a) RMSECV of DC prediction models; (b) R^2_{cv} of DC prediction models; (c) RPD of DC prediction models; (d) RMSECV of SC prediction models; (e) R^2_{cv} of SC prediction models; (f) RPD of SC prediction models; (g) RMSECV of BI prediction models; (h) R^2_{cv} of BI prediction models; (i) RPD of BI prediction models.

To eliminate the proportional differences in reflection intensity across different wavelengths and enhance the comparability of spectral data, the spectral data of the validation

set were first subjected to mean normalization. The processed spectra were then input into the established MLR model to predict six potato quality indicators. Scatter plots of measured versus predicted values (Figure 4a–f) were used to quantitatively assess model performance. For the prediction of DC (Figure 4a), the RMSEP was 0.010, with an R^2_P of 0.814, indicating good predictive performance for DC. For SC, the RMSEP was 0.012 with $R^2_P = 0.784$ (Figure 4b). For L^* , RMSEP = 1.287 and $R^2_P = 0.813$ (Figure 4c). For a^* , RMSEP = 0.594 and $R^2_P = 0.739$ (Figure 4d), which was the lowest among the color parameters, possibly due to the complex pigment metabolism in potato tubers. For b^* , the model achieved the highest $R^2_P = 0.936$ (Figure 4e), indicating very good predictive performance for yellowness. For BI, $R^2_P = 0.853$ (Figure 4f), indicating reliable prediction of browning degree. Overall, the predicted values agreed well with the measured values for both potato cultivars. These results demonstrate that the MLR models with mean normalization can effectively capture the correlation between Vis/NIR spectral data and quality indicators, providing a reliable approach for non-destructive quality prediction. To further evaluate the predictive reliability of the optimal MLR models, a comprehensive diagnostic analysis was carried out. Residual plots exhibited no obvious systematic trends or heteroscedasticity, verifying that the assumptions of linear regression were satisfied. Bias values for all six quality indicators were close to zero, ranging from -0.008 to 0.052 . Regression slopes varied between 0.91 and 1.04 , with intercepts near zero, demonstrating good agreement between predicted and measured values. According to standard RPD classification criteria, the RPD values of DC (2.236), L^* (2.148), a^* (2.001) and b^* (2.905) were greater than 2.0, implying that these models are suitable for quantitative screening applications. By contrast, the RPD values of SC (1.946) and BI (1.732) were below 2.0, indicating that their corresponding models are only appropriate for trend estimation rather than accurate quantification. Collectively, these analyses support a more rigorous model evaluation framework instead of relying on R^2 alone. To evaluate the stability of the developed models, cross-validation results across all folds were analyzed. For each quality indicator, RMSECV values were closely matched to their corresponding RMSEC values (Tables S1–S6), revealing that the models exhibited no severe overfitting on the current dataset. To contextualize the performance of the proposed system, a comparison with a previously reported Vis/NIR study on potato quality prediction is provided (Table S7) [33–35]. The prediction accuracies achieved in this study ($R^2_P = 0.739$ – 0.936) are comparable to those reported using a portable spectrometer. For instance, Escuredo et al. [12] adopted a commercial portable NIR device for potato quality estimation and reported R^2 values of 0.74 – 0.98 for moisture-related parameters. This comparison suggests that the selected wavebands of the proposed 12-channel system capture sufficient quality-related spectral information to support rapid screening applications.

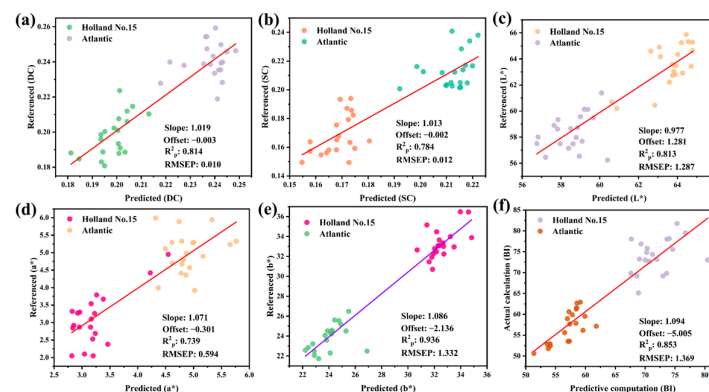


Figure 4. Comparison between predicted values and actual values of six potato quality indicators by the MLR model with normalization preprocessing. (a) Prediction results of DC; (b) Prediction

results of SC; (c) Prediction results of L^* ; (d) Prediction results of a^* ; (e) Prediction results of b^* ; (f) Prediction results of BI.

4. Conclusions

Real-time and non-destructive quality monitoring is critical for potato postharvest management and market competitiveness. In this study, a low-cost 12-channel Vis/NIR wireless spectral sensing system was developed for the real-time, non-destructive prediction of potato quality and accurate detection of quality traits. Six key indices including DC, SC, and color parameters were quantitatively analyzed using a prediction model based on mean normalization and MLR. The R^2_F values of DC, L^* , and b^* reached 0.814, 0.813, and 0.936, respectively, demonstrating the superior prediction performance of the mean-normalized MLR model. RPD values greater than 2 for DC, L^* , a^* , and b^* further verified that the model could meet practical detection requirements. The proposed wireless sensing system was thus validated in terms of repeatability, stability, and prediction performance. Compared with mainstream studies and traditional detection platforms (Table S7), the proposed system exhibits distinct innovative research contributions and practical advantages. First, the system adopts low-cost integrated spectral sensors, which greatly reduces hardware investment and breaks the high-cost barrier of traditional spectrometers for potato postharvest quality evaluation. Second, wireless data transmission and cloud-based processing are realized, supporting long-term, unattended, and dynamic monitoring in temperature-controlled environments tailored to potato postharvest storage and circulation scenarios. Third, the optimized MLR model is embedded into the sensing hardware, enabling real-time in-situ prediction and eliminating dependence on laboratory environments and offline analysis, which fills a key research gap existing in most laboratory-based model development for potato postharvest quality detection. Overall, this study delivers a novel low-cost, scalable platform for potato quality assessment under controlled conditions, and provides a valuable technical reference for the design of wireless, embedded non-destructive testing systems for horticultural postharvest applications. For the proposed 12-channel discrete-wavelength system, mean normalization is recommended as the preferred preprocessing method. Despite these limitations, the low-cost 12-channel wireless sensing system developed in this work can achieve rapid quantitative screening of core potato quality indicators under stable conditions. This platform provides a complete proof-of-concept for portable, embedded non-destructive detection and lays a solid foundation for subsequent on-site postharvest monitoring research. Nevertheless, this study has several limitations. Experiments were conducted with only two cultivars, without field validation under ambient light or temperature fluctuations. The influence of peel thickness and surface defects on spectral prediction was not quantitatively evaluated. The AS7262/AS7263 sensors miss the stronger absorption bands of starch and water in the 900–1400 nm region. Additionally, the models lack verification on fully independent external sample batches. Correspondingly, future research will first conduct field experiments under varying ambient light and temperature conditions and develop temperature compensation algorithms; second, establish correction models to eliminate spectral interference caused by varying peel thickness and surface defects; third, expand the spectral detection range to the 900–1400 nm short-wave infrared region; fourth, perform external validation using potato samples from distinct production batches and harvest seasons.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/digital6030065/s1>, Figure S1: Reflectance spectra of all potato samples acquired by a 12-channel spectral sensor after MSC normalization; Figure S2: Reflectance spectra of all potato samples acquired by a 12-channel spectral sensor after SNV processing; Figure S3: Reflectance spectra of all potato samples acquired by a 12-channel spectral sensor after SNV normalization; Figure S4: Visualization of the performance of potato quality index prediction models (PLSR, MLR, SVM) established with different preprocessing methods. (a) RMSECV of L^* prediction models; (b) R2CV of L^* prediction models; (c) RPD of L^* prediction models; (d) RMSECV of b^* prediction models; (e) R2CV of b^* prediction models; (f) RPD of b^* prediction models; (g) RMSECV of a^* prediction models; (h) R2CV of a^* prediction models; (i) RPD of a^* prediction models; Figure S5: Visualization graph; Table S1: Performance of PLSR, MLR, SVM and SNV Norm models for DC prediction using calibration set data with Original, Norm, SNV, SNV Norm and MSC Norm spectral preprocessing; Table S2: Performance of PLSR, MLR, SVM and SNV Norm models for SC prediction using calibration set data with Original, Norm, SNV, SNV Norm and MSC Norm spectral preprocessing; Table S3: Performance of PLSR, MLR, SVM and SNV Norm models for L^* prediction using calibration set data with Original, Norm, SNV, SNV Norm and MSC Norm spectral preprocessing; Table S4: Performance of PLSR, MLR, SVM and SNV Norm models for a^* prediction using calibration set data with Original, Norm, SNV, SNV Norm and MSC Norm spectral preprocessing; Table S5: Performance of PLSR, MLR, SVM and SNV Norm models for b^* prediction using calibration set data with Original, Norm, SNV, SNV Norm and MSC Norm spectral preprocessing; Table S6: Performance of PLSR, MLR, SVM and SNV Norm models for BI prediction using calibration set data with Original, Norm, SNV, SNV Norm and MSC Norm spectral preprocessing; Table S7: Comparison of the proposed system with conventional potato quality detection methods.

Author Contributions: C.L.: Writing—review & editing, Writing—original draft, Software, Data curation, Validation, Formal analysis. R.Z.: Writing—review & editing, Writing—original draft, Validation, Supervision, Conceptualization, Data curation, Methodology. W.Z.: Visualization, Software, Formal analysis. Y.G.: Resources, Project administration, Methodology, Funding acquisition. Y.D.: Supervision, Investigation, Formal analysis. T.S.: Visualization, Methodology, Supervision. W.L.: Project administration, Funding acquisition, Formal analysis, Resources. X.X.: Writing—review & editing, Project administration, Funding acquisition, Resources, Formal analysis, Conceptualization. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: This research is supported by the Inner Mongolia Autonomous Region Potato Industry Metrology Testing Center Project and Xinjiang Key Laboratory of Agro-products Quality & Safety (xjnkwdzc-2025002-09-kt8).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Khazaeli, S.; Kalvandi, R.; Sahebi, H. A multi-level multi-product supply chain network design of vegetables products considering costs of quality: A case study. *PLoS ONE* **2024**, *19*, 25. <https://doi.org/10.1371/journal.pone.0303054>.
2. Liu, P.; Zhang, P.; Ni, F.; Hu, Y. Feasibility of nondestructive detection of apple crispness based on spectroscopy and machine vision. *J. Food Process Eng.* **2021**, *44*, 10. <https://doi.org/10.1111/jfpe.13802>.
3. Shang, J.; Tan, T.; Feng, S.; Li, Q.; Huang, R.; Meng, Q. Quality attributes prediction and maturity discrimination of kiwifruits by hyperspectral imaging and chemometric algorithms. *J. Food Process Eng.* **2023**, *46*, 10. <https://doi.org/10.1111/jfpe.14348>.

4. He, H.J.; Wang, Y.; Zhang, M.; Wang, Y.; Ou, X.; Guo, J. Rapid determination of reducing sugar content in sweet potatoes using NIR spectra. *J. Food Compos. Anal.* **2022**, *111*, 104641. <https://doi.org/10.1016/j.jfca.2022.104641>.
5. Tu, H.Y.; Huang, D.M.; Huang, X.Y.; Aheto, J.H.; Yi, R.; Yu, W.; Ji, L.; Shuai, N.; Xu, M.Q. Detection of browning of fresh-cut potato chips based on machine vision and electronic nose. *J. Food Process. Eng.* **2021**, *44*, 10. <https://doi.org/10.1111/jfpe.13631>.
6. Feng, L.; Hou, T.; Zhang, B. A noninvasive method for detecting frozen injuries in potatoes based on electrical impedance spectroscopy. *J. Food Process. Eng.* **2021**, *44*, 6. <https://doi.org/10.1111/jfpe.13682>.
7. Semyalo, D.; Kim, Y.; Omia, E.; Arief, M.A.A.; Kim, H.; Sim, E.Y.; Kim, M.S.; Baek, I.; Cho, B.K. Nondestructive identification of internal potato defects using visible and short-wavelength near-infrared spectral analysis. *Agriculture* **2024**, *14*, 17. <https://doi.org/10.3390/agriculture14112014>.
8. Wang, Y.; Han, M.; Xu, Y.; Wang, X.; Cheng, M.; Cui, Y.; Xiao, Z.; Qu, J. Effect of potato peel on the determination of soluble solid content by visible near-infrared spectroscopy and model optimization. *Anal. Methods* **2023**, *15*, 3854–3862. <https://doi.org/10.1039/d3ay00774j>.
9. Chaukhande, P.; Luthra, S.K.; Patel, R.N.; Padhi, S.R.; Mankar, P.; Mangal, M.; Ranjan, J.K.; Solanke, A.U.; Mishra, G.P.; Mishra, D.C.; et al. Development and validation of near-infrared reflectance spectroscopy prediction modeling for the rapid estimation of biochemical traits in potato. *Foods* **2024**, *13*, 1655. <https://doi.org/10.3390/foods13111655>.
10. Wang, F.; Wang, C. Improved model for starch prediction in potato by the fusion of near-infrared spectral and textural data. *Foods* **2022**, *11*, 8. <https://doi.org/10.3390/foods11193133>.
11. Guo, Y.; Zhang, L.; Li, Z.; He, Y.; Lv, C.; Chen, Y.; Lv, H.; Du, Z. Online detection of dry matter in potatoes based on visible near-infrared transmission spectroscopy combined with 1d-CNN. *Agriculture* **2024**, *14*, 14. <https://doi.org/10.3390/agriculture14050787>.
12. Escuredo, O.; Meno, L.; Rodriguez-Flores, M.S.; Seijo, M.C. Rapid estimation of potato quality parameters by a portable near-infrared spectroscopy device. *Sensors* **2021**, *21*, 12. <https://doi.org/10.3390/s21248222>.
13. Wang, S.; Yan, J.; Tian, S.; Tian, H.; Xu, H. Vis/NIR model development and robustness in prediction of potato dry matter content with influence of cultivar and season. *Postharvest. Biol. Technol.* **2023**, *197*, 112202. <https://doi.org/10.1016/j.postharvbio.2022.112202>.
14. Liu, Z.; Li, W.; Zhai, X.; Li, X. Combination of precooling with ozone fumigation or low fluctuation of temperature for the quality modifications of postharvest sweet cherries. *J. Food Process Preserv.* **2021**, *45*, 15. <https://doi.org/10.1111/jfpp.15504>.
15. Lopin, P.; Nawsang, P.; Laywisadkul, S.; Lopin, K.V. Evaluation of low-cost multi-spectral sensors for measuring chlorophyll levels across diverse leaf types. *Sensors* **2025**, *25*, 2198. <https://doi.org/10.3390/s25072198>.
16. Nascimento, R.F.D.; Canteri, M.H.G.; Rodrigues, S.A.; Bittencourt, J.V.M. Optimization of processing parameters to control maillard browning in ready-to-eat processed potatoes. *Food Sci. Technol. Int.* **2021**, *27*, 764–775. <https://doi.org/10.1177/1082013220984295>.
17. Rouxinol, M.I.; Martins, M.R.; Murta, G.C.; Barroso, J.M.; Rato, A.E. Quality assessment of red wine grapes through NIR spectroscopy. *Agronomy* **2022**, *12*, 16. <https://doi.org/10.3390/agronomy12030637>.
18. Wang, M.; Zhang, R.; Wu, Z.; Xiao, X. Flexible wireless in situ optical sensing system for banana ripening monitoring. *J. Food Process. Eng.* **2023**, *46*, 9. <https://doi.org/10.1111/jfpe.14474>.
19. Wang, M.; Wang, B.; Zhang, R.; Wu, Z.; Xiao, X. Flexible vis/NIR wireless sensing system for banana monitoring. *Food Qual. Saf.* **2023**, *7*, 11. <https://doi.org/10.1093/fqsafe/fyad025>.
20. Tugnolo, A.; Pampuri, A.; Giovenzana, V.; Casson, A.; Guidetti, R.; Beghi, R. Test of a light emitting diode fully integrated pre-prototype spectrometer for rapid evaluation of table tomato (*solanum lycopersicum* L., Marinda f1) quality. *J. Near Infrared Spectrosc.* **2022**, *30*, 279–287. <https://doi.org/10.1177/09670335221119721>.
21. Xiao, Z.; Xu, Y.; Wang, X.; Wang, Y.; Qu, J.; Cheng, M.; Chen, S. Relationship between optical properties and internal quality of potatoes during storage. *Food Chem.* **2024**, *441*, 8. <https://doi.org/10.1016/j.foodchem.2023.138334>.
22. Pedrosa, V.M.D.; Izidoro, M.; Paythosh, S.; Dungan, R.S.; Olsen, N.; Spear, R.; de Almeida Teixeira, G.H. The relationship between respiration rate and quality parameters of russet potatoes during long-term storage. *Am. J. Potato Res.* **2025**, *102*, 93–105. <https://doi.org/10.1007/s12230-025-09977-7>.
23. Yu, Y.; Han, F.; Huang, Y.; Xiao, L.; Cao, S.; Liu, Z.; Thakur, K.; Han, L. Physicochemical properties and molecular structure of starches from potato cultivars of different tuber colors. *Starch-Starke* **2022**, *74*, 11. <https://doi.org/10.1002/star.202200096>.
24. Xiao, Q.; Bai, X.; He, Y. Rapid screen of the color and water content of fresh-cut potato tuber slices using hyperspectral imaging coupled with multivariate analysis. *Foods* **2020**, *9*, 16. <https://doi.org/10.3390/foods9010094>.

25. Hssaini, L. Controlling enzymatic browning in dried figs (*figus carica* l.) Through chemical treatments and optimized storage conditions. *Meas. Food* **2025**, *18*, 100226. <https://doi.org/10.1016/j.meafuo.2025.100226>.
26. Ren, W.; Jiang, Q.; Qi, W. Research progress in near-infrared spectroscopy for detecting the quality of potato crops. *Chem. Biol. Technol. Agric.* **2025**, *12*, 13. <https://doi.org/10.1186/s40538-025-00747-5>.
27. Peraza-Aleman, C.M.; Lopez-Maestresalas, A.; Jaren, C.; Rubio-Padilla, N.; Arazuri, S. A systematized review on the applications of hyperspectral imaging for quality control of potatoes. *Potato Res.* **2024**, *67*, 1539–1561. <https://doi.org/10.1007/s11540-024-09702-7>.
28. Chappelle, E.W.; Kim, M.S.; McMurtrey, J.E. Ratio analysis of reflectance spectra (rars)—An algorithm for the remote estimation of the concentrations of chlorophyll-a, chlorophyll-b, and carotenoids in soybean leaves. *Remote Sens. Environ.* **1992**, *39*, 239–247. [https://doi.org/10.1016/0034-4257\(92\)90089-3](https://doi.org/10.1016/0034-4257(92)90089-3).
29. Cadondon, J.G.; Ong, P.M.B.; Vallar, E.A.; Shiina, T.; Galvez, M.C.D. Chlorophyll-a pigment measurement of spirulina in algal growth monitoring using portable pulsed LED fluorescence lidar system. *Sensors* **2022**, *22*, 19. <https://doi.org/10.3390/s22082940>.
30. Santabarbara, S.; Carbonera, D. Carotenoid triplet states associated with the long-wavelength-emitting chlorophyll forms of photosystem i in isolated thylakoid membranes. *J. Phys. Chem. B* **2005**, *109*, 986–991. <https://doi.org/10.1021/jp047077k>.
31. Wu, Z.; Ouyang, G.; Shi, X.; Ma, Q.; Wan, G.; Qiao, Y. Absorption and quantitative characteristics of c-h bond and o-h bond of NIR. *Opt. Spectrosc.* **2014**, *117*, 703–709. <https://doi.org/10.1134/S0030400X1411023X>.
32. Yan, C. A review on spectral data preprocessing techniques for machine learning and quantitative analysis. *iScience* **2025**, *28*, 42. <https://doi.org/10.1016/j.isci.2025.112759>.
33. Su, W.H.; Xue, H. Imaging spectroscopy and machine learning for intelligent determination of potato and sweet potato quality. *Foods* **2021**, *10*, 16. <https://doi.org/10.3390/foods10092146>.
34. Bilgin, A.B.; Vega-Castellote, M.; Entrenas, J.A.; Torres-Rodríguez, I.; Aykas, D.P.; Basaran, P.; Pérez-Marín, D. Comparative evaluation of portable and benchtop NIR spectroscopy and hyperspectral imaging for detecting honey adulteration. *Sensors* **2026**, *26*, 2750. <https://doi.org/10.3390/s26092750>.
35. Valme, D.; Rassõlkin, A.; Liyanage, D.C. From ADAS to material-informed inspection: Review of hyperspectral imaging applications on mobile ground robots. *Sensors* **2025**, *25*, 2346. <https://doi.org/10.3390/s25082346>.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.