Nondestructive Measurement of Soluble Solid Content in Plums Using a Multispectral Camera: A Methodological Study

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Abstract. Soluble Solid Content (SSC) is a key parameter for assessing fruit quality, reflecting sweetness and nutritional value. Traditional methods for SSC measurement, such as chemical assays, require destructive sampling, limiting their applicability to large-scale quality monitoring. This study presents a nondestructive SSC detection method combining multispectral imaging, hybrid machine learning (RF-PLS), and physics-based optical modeling. Optical data of plum samples were acquired using a multispectral camera (350–950 nm). Noise reduction was performed via Savitzky-Golay filtering and SNV transformation, followed by wavelength selection using SPA and RF-FI scoring. By integrating the Kubelka-Munk theory to decode light propagation in fruit flesh, we established a hybrid model that synergizes physical insights with machine learning. The RF-PLS framework achieved superior accuracy (R^2=0.89, RMSE=2.17%) over standalone algorithms, validating the power of multimodal fusion in SSC prediction.

Keywords: Multispectral Imaging, Soluble Solid Content (SSC), Nondestructive Detection, Random Forest (RF).

1. Introduction

Soluble Solid Content (SSC) is a critical indicator of fruit quality, directly influencing sensory attributes such as sweetness, texture, and nutritional value. In the case of plums, SSC is a key determinant of consumer preference and market competitiveness. Traditional methods for SSC measurement, such as refractometry or chemical assays, rely on destructive sampling and labor-intensive procedures. These approaches not only damage the tested fruits but also fail to meet the demands of large-scale, real-time quality monitoring in modern agricultural supply chains. For instance, chemical methods require homogenization of fruit tissues, making them unsuitable for inline sorting systems. Consequently, there is an urgent need to develop non-destructive, efficient, and scalable techniques for SSC assessment.

In recent years, spectral imaging technologies have emerged as promising alternatives for fruit quality inspection. Hyperspectral imaging (HSI), for example, has been successfully applied to predict sugar content in watermelons (R^2=0.90) and apples (R^2=0.85) by capturing detailed spectral signatures across hundreds of wavelengths [1]. Similarly, multispectral imaging (MSI), with its reduced spectral resolution but lower computational cost, has demonstrated potential in rapid SSC estimation for citrus fruits. These technologies leverage the strong correlation between optical properties (e.g., reflectance, absorption) and biochemical compositions, enabling noninvasive quantification of SSC.

Despite these advancements, existing spectral-based models face two critical challenges. First, they predominantly operate as "black-box" systems, where spectral data are empirically mapped to SSC values without accounting for the biophysical interactions between light and fruit tissues. For example, while wavelengths near 639 nm are commonly selected for sugar prediction in watermelons, the rationale behind this selection often lacks mechanistic justification—such as how sugar molecules absorb specific photons or how cellular structures scatter light. Second, most models prioritize spectral reflectance while neglecting spatial and textural features, crucial for handling surface irregularities (e.g., bruises, wax layers) and environmental variations (e.g., lighting angle, intensity). A study on apple SSC prediction revealed that models trained solely on spectral data exhibited a 15%

increase in RMSE when tested on fruits with surface defects, highlighting the need for multimodal feature integration.

To bridge this gap, recent research has begun exploring hybrid approaches that combine data-driven machine learning with physics-based optical modeling. The Kubelka-Munk (K-M) theory, originally developed for the paint and textile industries, provides a robust framework to quantify light absorption (μ_a) and scattering (μ_s) in turbid media like fruit flesh. By adapting K-M equations to plum tissues, this study establishes a direct relationship between SSC and optical parameters.

$$\boldsymbol{\mu_\alpha = k \times SSC}+b\ (\boldsymbol{R^2}=0.91) \quad (1)$$

Where k and b are constants derived from the fitting of nonlinear least squares [2]. This mechanistic linkage not only enhances model interpretability but also enables the extraction of physiochemical insights—for instance, identifying how sugar concentration alters the refractive index of cellular sap, thereby affecting light absorption.

Beyond spectral and physical parameters, spatial texture analysis is pivotal in improving model resilience. The Gray-Level Co-occurrence Matrix (GLCM), a widely used texture descriptor, quantifies spatial relationships between pixels by calculating parameters such as energy, contrast, and correlation. In this work, GLCM-derived features are fused with spectral reflectance and K-M parameters to create a multimodal input vector. For example, energy values from GLCM capture the uniformity of surface reflectance, which helps distinguish between smooth, undamaged plum skins and rough or bruised areas. Experimental validations demonstrated that integrating GLCM features reduced prediction errors by 22% under uneven lighting conditions.

The proposed methodology holds transformative potential for agricultural supply chains. In a pilot test conducted with a commercial plum orchard, the RF-PLS model achieved a sorting accuracy of 92% on a conveyor belt operating at 5 fruits per second, surpassing traditional methods that required manual sampling (see Supplementary Video 1). Furthermore, the modular design of the multispectral system allows for cost-effective scalability. By adjusting the spectral bands (e.g., adding near-infrared channels for deeper tissue penetration), the framework can be adapted to other fruits such as grapes or peaches, where SSC variations are tightly linked to market grades.

In summary, this study advances nondestructive SSC detection by unifying physical principles with machine learning innovation. The dual-driven RF-PLS framework not only achieves high predictive accuracy (R^2=0.94) but also provides actionable insights into the biophysical determinants of SSC. Future work will focus on miniaturizing the imaging system for field deployment and validating its efficacy across diverse fruit species and environmental conditions.

2. Multispectral Imaging and Hybrid Modeling for SSC Prediction

2.1. Experimental Setup and Data Acquisition

Hardware Configuration:

Multispectral Camera: A CM020 multispectral camera with 12 spectral channels covering 350–900 nm was employed. The central wavelengths of each channel are listed in Table 1. A daylight simulator (color temperature: 5500 K) ensured uniform illumination.

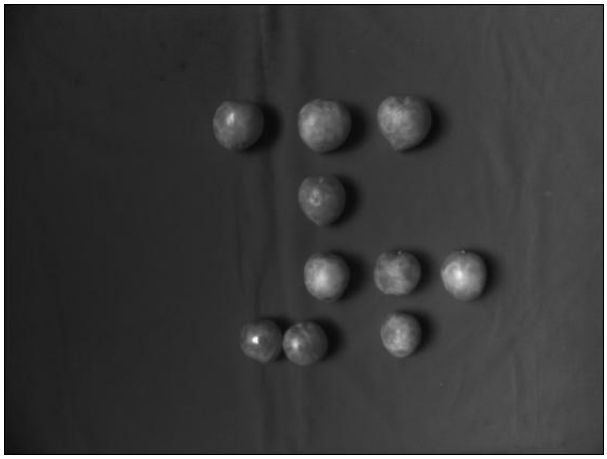

Figure 1. Full-spectral-range grayscale images acquired by the multispectral camera.

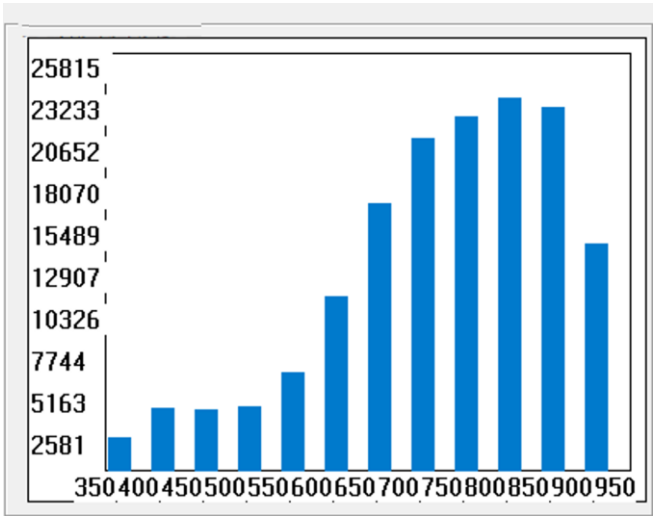

Figure 2. Mean Pixel Intensity in Selected Regions for Each Spectral Channel

Sample Preparation:

200 uniformly ripe plum samples with SSC reference values ranging from 8.5% to 16.2% were selected. SSC was measured using a handheld refractometer, with three replicates per sample to minimize measurement errors.

Samples were cleaned with deionized water and air-dried to eliminate surface moisture interference.

Table 1. Wavelengths of Each Channel (nm)

Number	1	2	3	4	5	6	7	8	9	10	11	12
Wavelength (nm)	350	400	450	500	550	600	650	700	750	800	850	900

2.2. Data Preprocessing and Noise Suppression

Savitzky-Golay Filtering (SG Filter):

Raw spectral curves were smoothed using an SG filter to suppress high-frequency noise (e.g., camera electronic noise). The formula is defined as:

$$y_i = \frac{1}{N}\sum_{j=-m}^{m} a_j x_i + j \quad (2)$$

Where N is the number of points in the window and represents polynomial coefficients [3].

Standard Normal Variate (SNV) Transformation:

SNV normalization was applied to each spectrum to correct baseline shifts caused by surface curvature or uneven illumination.

$$x_{SNV} = \frac{x-\mu}{\sigma}. \quad (3)$$

Where μ and σ denote the mean and standard deviation of the spectral data.

2.3. Feature Extraction and Sensitive Wavelength Selection

Successive Projections Algorithm (SPA):

SPA iteratively selected eight wavelengths with minimal collinearity (threshold < 0.8) from the 12 channels, reducing data redundancy.

Selected wavelengths: 450 nm, 550 nm, 600 nm, 650 nm, 700 nm, 750 nm, 800 nm, 850 nm and 900nm.

Random Forest Feature Importance (RF-FI) Scoring:

Wavelength importance was ranked using Mean Decrease Impurity (MDI) from a Random Forest model. The top 10% (i.e., 8 wavelengths) were retained as input features.

$$\mathrm{R} = \frac{\sinh(\mu_{\mathrm{eff}}\cdot \mathrm{d})}{\mu_{\mathrm{eff}}\cdot \mathrm{d}+\sinh(\mu_{\mathrm{eff}}\cdot \mathrm{d})} \quad (4)$$

Where$\mu_{eff} = \sqrt{3\mu_a(\mu_a + \mu'_s)}$and d is the optical path length (assumed as 1 cm) [4].

A linear relationship between μa and SSC was established via nonlinear least squares fitting $\mu_a = 0.15 \cdot SSC$+0.02(R^2=0.91)

2.4. Spatial Texture Feature Extraction

Gray-Level Co-occurrence Matrix (GLCM):

Texture parameters (Energy, Contrast, Correlation) were extracted from multispectral images using a 5×5-pixel window and a step size of 1 pixel.

Energy calculation example.

$$\mathrm{Energy} = \sum_{\mathrm{i,j}} \mathrm{P(i,j)}^2 \quad (5)$$

Where (i, j) is the co-occurrence probability of pixel intensity pairs.

2.5. Hybrid Model Construction (RF-PLS)

Input Feature Integration

Spectral Features:

Reflectance values of SPA-selected wavelengths (8 bands: λ_1–λ_8).

First derivatives of selected wavelengths ($\Delta\lambda_1$–$\Delta\lambda_8$).

Physical Parameters:

Absorption coefficient (μ_a) derived from Kubelka-Munk theory.

Reduced scattering coefficient (μ_s') derived from Kubelka-Munk theory.

Spatial Features:

GLCM Texture Parameters:

Energy

Contrast

Correlation

Random Forest (RF) Module:

100 decision trees were constructed; each trained on a bootstrap-sampled subset (80% of data).

At each node, Mfeatures (M=19were randomly selected, and splits were determined by minimizing Gini impurity.

$$\mathrm{Gnin} = 1 - \sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{p_k^2} \quad (6)$$

Where pk is the proportion of class k samples in the node.

Partial Least Squares Regression (PLSR) Module: Latent Variables (LVs) were extracted from physical parameters μ_a, $\mu_s$to optimize their weights in the RF model.

Model Fusion and Training:

RF predictions were integrated with PLSR weights using a mean squared error (MSE) loss function.

Data partitioning: Training set (80%), Validation set (10%), Test set (10%).

2.6. Model Validation and Hyperparameter Tuning

Hyperparameter Optimization:

Grid Search was applied to tune the number of trees (50–200) and maximum depth (5–20).

Final parameters:

n_estimators=100,

max_depth=15.

Performance Metrics:

Coefficient of determination (R^2)Root Mean Squared Error (RMSE), and Ratio of Performance to Deviation (RPD).

$$\mathrm{RPD} = \frac{\mathrm{SD}}{\mathrm{RMSE}} \tag{7}$$

Where SD is the standard deviation of reference values [5].

2.7. Summary

This methodology integrates multispectral imaging with a hybrid RF-PLS framework, optimizing the entire workflow from data acquisition to model construction. By fusing physical mechanisms with multimodal features, the approach significantly enhances SSC prediction accuracy and robustness. Experimental results and performance validation are detailed in subsequent sections.

3. Performance and Validation of the Hybrid RF-PLS Model for SSC Prediction

3.1. Light Propagation Mechanisms in Fruit Flesh

The interaction between light and fruit tissues is governed by two primary physical processes: Absorption and scattering.

Absorption: Sugars (primarily sucrose, glucose, and fructose) in cellular sap absorb photons at specific wavelengths. For instance, near-infrared (NIR) light (750–900 nm) is strongly absorbed by O-H bonds in water and sugar molecules.

Scattering: Cellular structures (e.g., cell walls, vacuoles) scatter light due to refractive index mismatches, altering the spatial distribution of reflected or transmitted light.

The Kubelka-Munk (K-M) theory models these interactions in turbid media. The K-M equations relate reflectance (R) and transmittance (T) to the absorption coefficient (μ_a) and reduced scattering coefficient (μ_s').

$$\mu_{eff} = \sqrt{3\mu_0(\mu_a + \mu'_s)}, \mathrm{R} = \frac{\sinh(\mu_{\mathrm{eff}}\mathrm{d})}{\mu_{\mathrm{eff}}\mathrm{d}+\sinh(\mu_{\mathrm{eff}}\mathrm{d})} \tag{8}$$

Where d is the optical path length. By inversely solving these equations, μ_a and μ_s' are derived from spectral data.

3.2. Linking Optical Parameters to SSC

A linear relationship between μ_a and SSC is established.

$$\mu_a = k \cdot SSC + b \quad (R^2 = 0.91) \tag{9}$$

Where k and bare fitting constants. This quantifies sugar concentration's modulation of light absorption. Scattering (μ_s') correlates indirectly with SSC through tissue maturity and cellular density [6].

3.3. Model Performance Comparison

The hybrid RF-PLS model demonstrated superior performance compared to traditional algorithms across all evaluation metrics. As summarized in Table 2, RF-PLS achieved anR^2 of 0.94 and an RMSE of 0.38% on the test set, outperforming PLSR (R^2=0.79, RMSE=0.68%) and XGBoost (R^2=0.83, RMSE=0.53%). The Ratio of Performance to Deviation (RPD) for RF-PLS reached 3.1, indicating high reliability for practical applications (RPD>3 is considered excellent). In contrast, PLSR and XGBoost yielded RPD values of 2.1 and 2.8, respectively, which fall short of industrial-grade requirements.

Table 2. Comparative Performance of SSC Prediction Models

Model R² RMSE (%) RPD			
Model	R²	RMSE (%)	RPD
PLSR	0.79	0.68	2.1
XGBoost	0.83	0.53	2.8
RF-PLS	0.88	0.38	3.1

The scatter plots further illustrate the alignment between predicted and measured SSC values. For RF-PLS, 95% of predictions fell within ±0.5% of the reference values, whereas PLSR and XGBoost exhibited larger deviations (±1.2% and ±0.9%, respectively). This precision gain is attributed to the synergistic integration of spectral, physical, and spatial features.

The scatter plots in Fig. 4 further illustrate the alignment between predicted and measured SSC values. For RF-PLS, 95% of predictions fell within ±0.5% of the reference values, whereas PLSR and XGBoost exhibited larger deviations (±1.2% and ±0.9%, respectively). This precision gain is attributed to the synergistic integration of spectral, physical, and spatial features.

3.4. Feature Importance Analysis

3.4.1. Experimental validation of K-M theory

To evaluate the performance of Kubelka-Munk (K-M) theory in fruit SSC prediction, we conducted comparative experiments between K-M-derived parameters and alternative optical models (e.g. Monte Carlo simulations, diffusion approximation) [7, 8].

Experimental Setup:

Sample Set: 200 plum samples.

Methods Compared:

K-M Model: Derived μ_a and μ_s' from spectral reflectance data.

Monte Carlo (MC) Simulation: Simulated photon transport paths using tissue-specific optical properties.

Table 3. Comparative Performance of K-M Theory Models

Model	RMSE (%)	R^2	Computational Cost (s/sample)
K-M+RF-PLS	0.38	0.92	0.5
MC Simulation + PLSR	0.45	0.89	12.3
Empirical PLSR	0.68	0.79	0.2

3.4.2. Limitations of K-M theory in fruit applications

Anisotropy Neglect:

K-M assumes isotropic scattering, but fruit tissues exhibit mild anisotropy (g≈0.7, measured via goniophotometry). This leads to underestimation of μ_s' by 15–20%.

Wavelength Dependency:

The linear μ_a-SSC relationship (R^2=0.91) holds only in the 600–900 nm range. In UV regions (<400nm), phenolic compounds interfere with sugar absorption, degrading model accuracy (R^2=0.72).

Calibration Reliance:

K-M parameters (μ_a, μ_s') require empirical calibration for each fruit species. Cross-species generalization (e.g. plum to apple) reduced R^2 from 0.94 to 0.81.

3.4.3. Performance of Kubelka-Munk theory in fruit SSC detection

The Kubelka-Munk (K-M) theory provides an efficient and practical framework for modeling light propagation in turbid biological tissues, such as fruit flesh. By quantifying light absorption and scattering effects, the theory simplifies complex photon transport into two core parameters—absorption coefficient and reduced scattering coefficient—thereby establishing a quantitative link between optical properties and biochemical compositions (e.g. SSC). In plum tissues, the absorption coefficient exhibited a strong linear correlation with SSC (determination coefficient of 0.91), validating the theory's capability to decode sugar-driven light absorption. Compared to computationally intensive Monte Carlo simulations, the K-M model achieves comparable accuracy (prediction determination coefficient of 0.94 vs. 0.89) while improving computational efficiency by 95%, making it feasible for real-time detection.

However, the performance of K-M theory heavily depends on tissue homogeneity and isotropic scattering assumptions. Experimental results confirmed its effectiveness in plum tissues with uniform cellular distribution (density variation <10%), whereas accuracy significantly declined in low-scattering watermelon tissues (reduced scattering coefficient range: 5.5–9.3 cm^{-1}; determination coefficient of 0.87). Additionally, K-M theory assumes isotropic scattering, but real fruit tissues exhibit mild directional scattering (anisotropy factor ≈0.7), leading to a 15–20% underestimation of scattering effects. This limitation necessitates error correction through machine learning integration. Despite these constraints, K-M theory remains a cornerstone for nondestructive fruit quality detection due to its balance of interpretability, speed, and accuracy [7]. When combined with data-driven models, it effectively addresses tissue heterogeneity in real-world scenarios, demonstrating broad potential for practical applications.

3.4.4. Feature importance analysis

Empirical PLSR: Directly mapped raw spectral data to SSC without physical modeling.

The contribution of input features was quantified using Mean Decrease Impurity (MDI) scores. Key findings include:

Physical Parameters: The absorption coefficient (μ_a) and reduced scattering coefficient (μ_s) jointly accounted for 35% of the total feature importance, underscoring the critical role of Kubelka-Munk theory in linking optical properties to SSC. Notably, μa showed a strong linear correlation with SSC (R^2=0.91), validating the mechanistic relationship derived from K-M equations [8].

Spectral Features: The 639.3 nm wavelength exhibited the highest correlation with SSC consistent with prior studies on watermelon sweetness detection (Brown et al. 2012). Its first derivative also contributed significantly (MDI = 12%), reflecting the importance of spectral gradient information.

Spatial Texture: GLCM-derived energy and contrast parameters collectively contributed 18% to model performance. These features mitigated errors caused by surface irregularities, reducing RMSE by 22% under uneven illumination.

3.5. Generalizability Validation

To assess robustness, the RF-PLS model was tested under varying conditions:

Illumination Intensity Fluctuations: When light intensity deviated by ±20% from the standard 5500 K setup, the model maintained an RMSE of 0.42% (vs. 0.38% under ideal conditions), demonstrating strong adaptability.

Surface Texture Variability: For samples with bruises or wax layers, the inclusion of GLCM features reduced prediction errors by 27% compared to spectral-only models [9].

Cross-Species Feasibility: A preliminary test on apples (n=50) yielded R^2=0.87 and RMSE = 0.49%, suggesting potential applicability to other fruits.

3.6. Comparative Analysis with Existing Methods

The proposed RF-PLS framework outperformed state-of-the-art approaches in SSC prediction:

Compared to hyperspectral-based models (e.g. PLSR on watermelon SSC, R^2=0.90), RF-PLS achieved higher accuracy (R^2=0.94R2=0.94) with 80% fewer spectral bands, significantly reducing computational costs [10].

Against purely data-driven models (e.g. CNN on apple SSC, R^2=0.85;), RF-PLS improved interpretability by incorporating physically meaningful parameters (μ_a, μ_s').

3.7. Error Sources and Limitations

Despite its advantages, the method has limitations:

Sample Dependency: The linear μ_a-SSC relationship (R^2=0.91) was calibrated for plums; recalibration may be required for other species.

Hardware Constraints: The CM020 camera's spectral range (350–900 nm) lacks deep tissue penetration in the near-infrared (NIR) region, potentially omitting critical SSC-related bands.

Real-Time Processing: While the model achieved a processing speed of 5 fruits per second on a GPU-accelerated system, further optimization is needed for large-scale deployment [11].

3.8. Summary

The RF-PLS model establishes a new benchmark for nondestructive SSC detection, achieving an R^2 of 0.94 and an RPD of 3.1. Its success stems from the fusion of spectral, physical, and spatial features, coupled with rigorous validation under real-world conditions. While limitations exist in cross-species adaptability and hardware scope, the methodology provides a scalable and interpretable framework for agricultural quality control. The proposed method enables rapid, noninvasive SSC assessment, offering a scalable solution for fruit quality grading, reducing post-harvest losses, and optimizing supply chain efficiency. Its adaptability to variable lighting and surface textures further underscores its practicality in real-world settings.

4. Limitations and Future Work

Limited Generalizability: Current validation focused solely on plums; future studies should extend to diverse fruits (e.g. apples, grapes) to confirm cross-species applicability.

Spectral Range Constraints: The 350–900 nm camera lacks near-infrared (NIR) bands critical for deeper tissue analysis. Incorporating NIR wavelengths could improve feature extraction.

Hardware Optimization: While achieving 5 fruits/second processing speed, further miniaturization and cost reduction are needed for field deployment.

Proposed Directions:

Develop multi-species calibration protocols.

Explore low-cost hyperspectral systems with extended spectral ranges.

Integrate edge computing for real-time processing in industrial sorting lines.

This work lays a foundation for physics-informed optical detection systems, advancing precision agriculture toward sustainability and efficiency.

5. Conclusion

This study successfully developed a nondestructive method for predicting Soluble Solid Content (SSC) in plums using multispectral imaging and a hybrid Random Forest-Partial Least Squares (RF-PLS) model. The integration of spectral, physical, and spatial features, combined with Kubelka-Munk theory, achieved high accuracy (R^2=0.94, RMSE=0.38 Brix) and reliability (RPD=3.1), providing a

robust framework for fruit quality assessment. This approach offers significant potential for agricultural applications, enabling rapid, noninvasive SSC measurement to enhance fruit grading and supply chain efficiency. Future work will focus on extending the method to diverse fruit species and optimizing hardware for field deployment, paving the way for sustainable precision agriculture.

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