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Use of near-infrared spectrometry in temperate fruit: A review

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Abstract: Near-Infrared (NIR) spectrometry has emerged as a promising tool for the non-destructive and rapid analysis of temperate fruit quality, maturity, and other parameters. The technique provides a wealth of information, including details of chemical composition, without damaging the fruit, making it a highly viable alternative to traditional methods. This paper reviews the recent research and applications of NIR spectrometry for fruit evaluation, highlighting its strengths and potential limitations. The analysis shows a significant potential for NIR spectrometry, especially when combined with machine learning and artificial intelligence to handle complex data and improve predictive models. The development of portable NIR spectrometers allows for *in-situ* quality assessment, expanding its applicability to various fields including on-site quality control. Despite the benefits, this review identifies key challenges including spectral complexity, fruit variability, and the influence of the external environment. Recommendations for future research include focusing on improving calibration and validation of models, increasing predictive accuracy, and developing user-friendly instruments. In addition, standardization of measurement procedures and analytical methods is needed to ensure comparability and reproducibility of results. Further research is needed to fully realize the full potential of NIR spectrometry in fruit quality control.

Keywords: NIR spectroscopy; temperate fruit; fruit evaluation; quality control; calibration and validation

Topic definition: NIR Spectroscopy and its application on temperate fruits. This scientific review focuses on the applications of the near-infrared (NIR) spectroscopy method in the context of temperate fruit species. NIR spectroscopy, a rapid and non-contact analytical method, is used in many fields, including food, and provides detailed data on the chemical composition and quality of samples (Porep et al. 2015). In the field of fruit products, it is an effective tool to evaluate quantitative and qualitative characteristics, such as maturity, sugar content, acidity, and others (Nicolaï et al. 2007; Hernández-Hierro et al. 2022; Pandiselvam et al. 2022; Fodor et al. 2023).

The use of NIR spectroscopy on fruit brings numerous advantages, including speed of analysis, minimal sample preparation, and the possibility of repeated measurements on the same sample without damage (Cattaneo, Stellari 2019). These characteristics make it an essential tool for monitoring and controlling storage processes, maturity, and fruit quality.

Although previous research has already provided many useful insights (Luypaert et al. 2007; Cortés

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et al. 2019; Pathmanaban et al. 2019), there are still areas that require further investigation. Therefore, this article focuses on an overview of research in the field of NIR spectroscopy on temperate fruit.

Importance of the topic and motivation for conducting the review. The motivation for investigating the application of NIR spectroscopy to temperate fruit species is multifaceted. As a fundamental part of the diet, temperate fruits require detailed assessment of quality, maturity, and nutritional parameters to ensure food safety (Nicolaï et al. 2007; Hernández-Hierro et al. 2022; Ye et al. 2022; Fodor et al. 2023). Traditional methods, while effective, can be laborious and potentially destructive. NIR spectroscopy offers a rapid and non-invasive solution, which optimizes control processes (He et al. 2022).

However, questions remain regarding the optimal methods and models for fruit evaluation, the influence of various factors on spectral characteristics, and the development of new technologies. Research can contribute to the development of new knowledge and improve food quality and safety, which supports the use of temperate fruits in the food industry.

Aim of this article. The aim of this article is to thoroughly evaluate the advances and developments in the field of NIR spectroscopy applied to temperate fruits. This task is motivated by the rapid progress and widespread use of NIR spectroscopy in the food industry, which requires an updated review of its applications and potential.

This review will focus on key aspects of the application of NIR spectroscopy to fruit and will compare the results obtained by NIR spectroscopy with traditional analytical methods. It will also evaluate the benefits and limitations of this technology.

Finally, this review will attempt to identify gaps, challenges, and opportunities for future research in the field of NIR spectroscopy on fruit. Our literature review will focus on research that could contribute to the further development and use of this technology to benefit the production and consumption of temperate fruits.

Principles of near-infrared spectroscopy. Near-Infrared spectroscopy, a technology based on the interaction of near-infrared radiation with a sample, is an effective tool for the rapid and contact-free evaluation of fruit composition and quality. The principle of the method is based on the use of specific absorption patterns of NIR radiation by different fruit components, such as sugars, acids, and other organic compounds (Uwadaira et al. 2018). For quantitative analysis, calibration models are used that correlate spectral data with reference values obtained by traditional analytical methods (Li et al. 2018b).

Advantages and limitations of this technology in fruit evaluation. One of the main benefits of NIR spectroscopy is its rapid and continuous measurement, which can be performed in-line, on-line, or at-line, thus being optimal for industrial use (Xie et al. 2008; Patel et al. 2016). This technology also offers the possibility of non-invasive measurement, which is critical for fruit quality assessment, as any sample damage can skew the results and affect the quality of the final product (Tian et al. 2018).

NIR spectroscopy offers many benefits for temperate fruit evaluation. Key advantages include:

Speed and efficiency: NIR spectroscopy allows for rapid and non-invasive fruit evaluation, saving time and resources. Single measurements with an NIR spectrometer provide comprehensive data on the chemical composition and quality of the fruit (Huang et al. 2020a; Minas et al. 2023).

Calibration of models: Proper use of NIR spectroscopy requires calibration of models, which involves collecting reference data and correlating them with NIR spectra. Proper calibration is key to obtaining accurate results (Marečková et al. 2022).

Contactless measurement: NIR spectroscopy allows for contactless measurement, minimizing physical interaction with the fruit and reducing the risk of damaging or contaminating it (Malvandi et al. 2022).

Multicomponent analysis: NIR spectroscopy allows the simultaneous analysis of different fruit components. This technology enables the quantification of various substances such as sugars, acids, vitamins, flavonoids, and others that influence the quality and nutritional value of fruit (Nader et al. 2017; del Río Celestino, Font 2022).

Wide application: NIR spectroscopy has many application in agriculture, food industry, and research. It is used for fruit evaluation at harvest, maturity control, quality management, and variety selection (Slaughter, Abbott 2004; Xie et al. 2008; Kumaravelu, Gopal 2015; Patel et al. 2016; Li et al. 2018a; Huang et al. 2020a; Li et al. 2021; Fodor et al. 2023).

However, NIR spectroscopy has certain limitations and challenges:

Need for calibration: Proper use of NIR spectroscopy requires calibration of models, which involves collecting reference data and correlating them with

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NIR spectra. Accurete calibration is key to obtaining accurate results (Tsuchikawa et al. 2022).

Influence of external factors: Various factors such as temperature, humidity, illumination, and external interaction with the fruit can affect NIR spectroscopy, which can influence the spectral characteristics and require appropriate correction procedures (Qu et al. 2015; Lin et al. 2009; Ying et al. 2009).

Limited penetration depth: NIR spectroscopy measures the interaction of light with the sample surface, which limits its ability to analyze the internal structure of the fruit. This can be problematic when evaluating parameters that change during fruit ripening and maturation (Lafuente et al. 2015; Lu, Lu 2017).

Detection of specific substances: NIR spectroscopy may be insensitive to some substances that are present in fruit at low levels, or that are difficult to detect (Cen, He 2007; Jiang et al. 2018).

The importance of instrument calibration and validation to ensure accurate results. The use of NIR spectroscopy presents certain challenges, including the need for careful calibration and validation of instruments, necessary both during initial setup and on an ongoing basis during operation, to compensate for potential influences of factors such as temperature, humidity, and other variables that may affect the results (Gao et al. 2010; Lohumi et al. 2015; Donis-González et al. 2022). Results can be affected by variability in fruit samples, including heterogeneity, changes in maturity, and other factors that influence NIR radiation absorption patterns (Tian et al. 2018). Ensuring quality control of measurements is necessary to maintain the accuracy and reliability of instruments, including proper detector settings, spectral calibration checks, and measurement accuracy. Calibration determines the relationship between the measured NIR spectra and reference values, which are generated based on a sufficient amount of reference samples (Wu, Sun 2013; Huang et al. 2020a; Hasanzadeh et al. 2022).

APPLICATION OF NIR SPECTROMETRY TO TEMPERATE ZONE FRUIT

Pome fruits

Apples. NIR spectrometry has demonstrated its potential for rapid and accurate evaluation of apple quality at the industrial level, including parameters such as sugar content, acidity, firmness, and colour (Patel et al. 2016; Nader et al. 2017; Zhang et al. 2019; Guo et al. 2020a; Marečková et al. 2022; Vlivert et al. 2023). This method has also been successfully applied to the estimation of apple composition, including antioxidants, and polyphenols (Pissard et al. 2018; Guo et al. 2020a). Chemometric methods such as partial least squares (PLSR) , support vector machine (SVM), multiple linear regression (MLR) have been used to accurately predict these parameters (Shunchang et al. 2011).

Calibration models were developed to determine the soluble solids content (SSC) in apples in the spectral range of 643.26–928.35 nm have been developed, with a correlation coefficient of 0.938, a calibration standard error of 0.38, a prediction standard error of 0.46, and a deviation of –0.0015 (Shunchang et al. 2011).

Spectroscopic methods were also successfully used to predict the flesh firmness of apple varieties 'Gala', 'Red Jonaprince', and 'Jonagored' with the coefficient of determination for calibration (R^2) and the ratio of prediction to deviation (RPD) exceeding values of 0.91 and 2.3, respectively. The highest R^2 and RPD values achieved were 0.94 and 2.6 with a calibration error of 5.87 N and cross-validation error of 6.75 N (Marečková et al. 2022).

A comparison of a portable NIR spectrometer and online NIR system for determination of SSC showed better results for the portable measurement mode with R^2 and root mean square error of prediction (RMSEP) values of 0.88 and 0.80 °Brix compared to the online mode with values of 0.82 and 1.01 °Brix (Sun et al. 2009).

For 'Gala', 'Honeycrisp', 'McIntosh', 'Jonagold', 'NY1', 'NY2', 'Red Delicious', and 'Fuji' apple varieties, a portable spectrophotometer was used with a measurement range of 300—1 100 nm and a resolution of 3 nm was used to evaluate parameters such as SSC and dry matter content (DMC) of fruits. R^2 values reached up to 0.9 for SSC and 0.92 for DMC with root mean square error (RMSE) values around 0.67% for SSC and 5.88 g/kg for DMC (Zhang et al. 2019).

Models for the determination DMC and SSC in apples were developed over a storage period of 10 weeks at 0.5 °C. Spectra were obtained using a portable spectrometer in the wavelength range 750–1065 nm. R^2 values reached 0.58 for SSC and 0.55 for DMC with RMSEP values less than 8% (Vlivert et al. 2023).

Cross-validation models for apple dry matter content reached R^2 values of up to 0.95. Three different commercial food scanners were used: SCiO™, F-750 Produce Quality Meter, and H-100F (Goisser et al. 2021).

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Hyperspectral imaging (HSI) and acoustic emission (AE) measurements were identified as effective methods for predicting some qualitative characteristics of the apple variety 'GoldRush'. HSI achieved better predictive capabilities than AE for firmness, TSS, and colour parameters (L^*, a^*, b^*) with ratio of prediction (RP) values of 0.92, 0.41, 0.83, 0.87, and 0.94 and RMSEP values of 4.32 (*N*), 1.78 (°Brix), 3.41, 2.28, and 4.29. AE achieved ratio of prediction (RP) values of 0.88, 0.74, 0.34, 0.37, and 0.81 and RMSEP values of 4.26 (*N*), 0.64 (°Brix), 4.69, 1.8, and 5.17 for firmness, TSS, and colour parameters (L^*, a^*, b^*) (Nader et al. 2017).

In a combined model using the competitive adaptive reweighted sampling (CARS), PLS, and mixed temperature compensation (MTC) methods, high efficiency was demonstrated in predicting various characteristics of apples (such as SSC, vit. C, titratable acidity (TA), and firmness) with RP values up to 0.9236 and RPD up to 2.604. A portable spectrometer was used to obtain NIR spectra of apples covering 590–1 200 nm (Guo et al. 2020a).

CARS-PLS models achieved optimal results in predicting SSC and water core rate in apples, reaching RP 0.9562 and 0.9808 and RMSEP 1.340% and 0.327 °Brix, respectively, when using a spectral range of 600–1 000 nm. The significant RPD value reached 3.720 and 4.845 for these parameters (Guo et al. 2020b).

A rapid and non-invasive determination of phenolic compound content and dry matter was performed on 20 apple varieties (Pissard et al. 2018). Calibration and validation models for predicting total phenolic compounds (TPC) and dry matter (DM) prediction showed high determination coefficients (R^2) for TPC, with values slightly higher for peel than for flesh (R^2val = 0.91 and 0.84; Pissard et al. 2018). For DM, the models also achieved high determination coefficients of determination and RPD, indicating accurate predictions (R^2 = 0.94, RPD = 4.8 for skin and R^2 = 0.94, RPD = 4.9 for flesh (Pissard et al. 2018).

Sugars in the growth stages of 'Gala' and 'Red Delicious' apple varieties were quantified using high performance liquid chromatography (HPLC). Sorbitol, the dominant sugar (40%), decreased to less than 10% after 59 days. Fructose increased from 40% to 50%. Calibration models were created using PLS to compare HPLC and reflectance spectra. NIR models predicted sugar content with R^2 between 0.60 and 0.96 (Larson et al. 2023).

Hyperspectral imaging (400–1000 nm) was used to evaluate the quality of 'Red Delicious' apples after 60 days of storage. pH was determined destructively. PLS analysis and Savitzky-Golay smoothing obtained RMSE 0.02 and 0.018 and R^2 0.980. ANN (artificial neural network) performed modelling of 9 optimal wavelengths with the best result (Golmohammadi et al. 2022).

Research focuses on the use of low-cost VIS-NIR HSI (386–1028 nm) for predicting the moisture content and pH of 'Pink Lady' apple variety at three ripening stages. HSI data analysis was performed using PLSR (partial least squares regression), MLR (multiple linear regression), kNN (k-nearest neighbour), DT (decision tree), and ANN (artificial neural network) algorithms. The analysis focused on 11 optimal features identified by the Bootstrap Random Forest method. The ANN algorithm provided the best performance with R^2 0.868 and RMSE 0.756 for MC and R^2 0.383 and RMSE 0.044 for pH (Kavuncuoglu et al. 2023).

Subsequently, Kavuncuoglu et al. (2023) confirmed the use of NIR spectrometry for predicting apple ripeness, thus optimizing harvesting and sales. Differentiation between apple varieties was investigated by He et al. (2007), who concluded its effectiveness based on spectral characteristics.

The correction of NIR spectra due to apple size was performed by studying the extinction coefficients, resulted in an improvement in the correlation coefficient (RP) from 0.769 to 0.869 and a reduction in the root mean square error of prediction (RMSEP) from 0.990 to 0.721 for smaller apples. For larger apples, RP increased from 0.787 to 0.932 and RMSEP decreased from 0.878 to 0.531 (Jiang et al. 2022).

NIR spectroscopy has also been successfully applied to the analysis of commercial apple juices. Quantitative relationships between spectra and juice properties, such as soluble solids content (SSC), titratable acidity (TA), and the SSC/TA ratio, were identified using the PLS regression method. The best model for predicting SSC (R^2 = 0.881, root mean square error of cross validation (RMSECV) = 0.277°Brix, and relative error (RE) = 2.37%) was obtained for spectra preprocessed by the first derivative and variable selection using the jack-knife method. The best model for TA (R^2 = 0.761, RMSECV = 0.239 g/L, and RE = 4.55%) was obtained for smoothed spectra in the 6224–5350 cm/range. The optimal model for the SSC/TA ratio (R^2 = 0.843, RMSECV = 0.113, and RE = 5.04%) was obtained

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for unprocessed spectra in the 6 224–5 350 cm^{-1} range (Włodarska et al. 2018).

NIR spectrometry is also used to identify and monitor pests (Gowen et al. 2007; Ekramirad et al. 2016; Adedeji et al. 2020; Ekramirad et al. 2022). This method is also effective in identifying resistant fruit varieties that can be distinguished by spectral characteristics (Jarolmasjed et al. 2019; Jarolmasjed et al. 2019).

Research by Hahn (2009) showed that NIR spectrometry can differentiate healthy fruit from fruit affected by fungal diseases.

NIR spectrometry is also used to detect physiological disorders in fruit, such as bruising or internal browning. The method can identify specific spectral signals associated with these disorders, allowing their rapid diagnosis and resolution (Lee et al. 2005; Mogollon et al. 2020; Baek et al. 2022; Tian et al. 2023).

Pears. Pears are another fruit where NIR spectroscopy has been successfully applied. It is effectively used to predict attributes such as flesh firmness, sugar content, and acidity in fruit, including pears. This has been confirmed by many studies (Fu et al. 2009; Khodabakhshian, Emadi 2017; Li et al. 2020; Mishra et al. 2021; Lu et al. 2022; Taghinezhad et al. 2023).

Spectral data of three pear varieties were analyzed using four different algorithms for assessing their firmness and soluble solids content (SSC). The PLS and SPA-PLS models were used to predict firmness and SSC, while Fisher LDA was used to discriminate between varieties. The most effective method turned was SPA-PLS with a correlation coefficient (R^2) of 0.9977 for firmness and 0.9924 for SSC. The accuracy of variety classification was 95.56% using Fisher LDA. SPA-PLS models had lower RMSEP values than PLS models, 0.062 653 for firmness and 0.03175 for SSC (Li et al. 2016).

An electronic nose (E-nose) can predict the firmness and SSC of the 'Xueqing' pear variety with high accuracy. The models achieved standard error of prediction (SEP) values of 0.41 for SSC with a correlation coefficient of 0.93 and SEP values of 3.12 with a coefficient of 0.94 for penetration force (CF). This method is more accurate than multiple linear regression (MLR), but low correlation with the E-nose signal was observed for acidity (Zhang et al. 2008).

The CARS-SPA method in combination with a hyperspectral imaging system is effective for the determination of SSC and firmness. A total of 160 pear samples were analyzed. The PLS method was used to analyze the spectral data. The correlation coefficient and RMSEP for the CARS-SPA-PLS models were 0.876, 0.491 for SSC, and 0.867, 0.721 for firmness (Fan et al. 2015a).

The joint use of CARS and SPA methods for effective variable selection significantly improved the predictive ability of calibration models for determining soluble solids content (SSC) and pear firmness (Fan et al. 2015b).

Subsequent studies focused on predicting the SSC content in pears and classifying surface positions (illuminated and shaded sides) using spectral data. Different types of models (specific model for each position, global models for all positions, average spectral model) and different spectral regions (550–950 nm, 550–780 nm, 780–950 nm, 550–700 nm) were used. In the measurement of 'Korla' pears, the best prediction of SSC content was obtained using the model based on effective wavelengths (EWs) for each pear position, with a correlation coefficient of the prediction set (RPre) of 0.9408 for the illuminated side and 0.9463 for the shaded side. The classification model based on 68 EWs selected from the range of 550-950 nm achieved a correct classification of 97.78% in the calibration set and 96.67% in the prediction set. The accuracy of predicting SSC content and classifying surface positions is influenced by the surface characteristics of pears, especially the skin colour (Tian et al. 2018).

Near-infrared spectroscopy (NIR) is also used in fruit variety control and identification of fruit varieties. The study by Li et al. (2016) investigated the use of NIR spectroscopy to distinguish varieties. The results showed that NIR spectroscopy is able to distinguish different varieties based on their chemical profiles.

NIR spectroscopy provided 100% accuracy in identifying 'Zaosu' and 'Dangshansuli' varieties. The prediction of soluble solids content (SSC) and titratable acidity for the 'Dangshansuli' variety achieved a residual predictive deviation (RPD) of 3.272 and 2.239, surpassing the predictive model for the 'Zaosu' variety (RPD: 1.407 and 1.471) (Lu et al. 2022).

Using interval partial least squares and covariate selection, the bias was reduced from 1.31% to 0.19% for moisture content (MC) and from –0.62% to 0.07% for SSC, and the root mean square error of prediction (RMSEP) from 1.44% to 0.58% for MC and from 0.90% to 0.63% for SSC (Mishra et al. 2021).

For 'Huangguan' pears, the prediction model for phosphorus content in pulp and peel was significantly successful, achieving values of R^2 = 0.843 and

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RPD = 1.857 (pulp) and R^2 = 0.991 and RPD = 7.470 (peel) in the calibration set, and R^2 = 0.989 and RPD = 7.041 (pulp) and R^2 = 0.974 and RPD = 4.414 (peel) in the validation set (Li et al. 2023).

Visible and near-infrared (VIS/NIR) spectroscopy allows prediction of fruit juiciness, using various methods of spectral preprocessing. A spectrometer with wavelengths of 650–1100 nm was used to collect spectra. The PLS model based on 19 characteristic variables processed by the linear regression correction combined with spectral ratio (LRC-SR) method achieved the best results, reaching an external validation coefficient of determination (R^2) of 0.93 and a root mean square error of validation (RMSEV) of 0.97% (Wang et al. 2020).

In the field of identification of physiological defects in fruit, the method of hyperspectral image analysis in the infrared spectrum (950–1 650 nm) is applied together with a classification algorithm based on the *F*-value. This method allowed the detection of bruises on pears with an accuracy of up to 92% due to the optimal ratio of wavelengths (1 074 nm and 1 016 nm: R1074/R1016) (Lee et al. 2014).

The studies by Han et al. (2006) and Hao et al. (2023) showed high accuracy in the detection of browncore on pears using NIR spectroscopy, which is important for their quality assessment.

For online and dynamic browning detection, the Ocean Optics INC, QE65Pro spectrometer with wavelengths of 361–1 165 nm and a spectral resolution of approximately 0.8 nm was used. The data was analyzed using partial least squares discriminant analysis (PLS-DA), support vector machine (SVM) method, and 1D convolutional neural networks (1D-CNN). The results show 100% accuracy in distinguishing browning pears from healthy samples for 1D-CNN models, with PLS-DA achieving 97.32% and SVM achieving 98.66% accuracy (Hao et al. 2023).

Stone fruits

Plums. Several studies focus on the application of NIR spectrometry for quality assessment of temperate fruit. Parameters such as sugar content, acidity, and firmness, are the subjects of research (Paz et al. 2008; Louw, Theron 2010; Li et al. 2017; Vlaic et al. 2018; Guo et al. 2022; Fodor et al. 2023).

One study conducted by Vlaic et al. (2018) focused on the quantification of individual sugars in plum juice using HPLC and FT-MIR methods, with sugar contents ranging from 0.26% to 3.73% for fructose, 1.43% to 1.10% for glucose, and 0.01% to 10.19% for sucrose.

Research by Paz et al. (2008) used NIR spectrometry to develop calibration models for different varieties of plum (*Prunus salicina* L.). For total soluble solids (SSC), SECV was 0.77 °Brix and R^2 was 0.83, while for firmness, SECV was 2.54 N and R^2 was 0.52.

Costa and de Lima (2013) conducted a study to predict the soluble solids content (SSC) and pH, where the correlation coefficient (R^2) was 0.95 and 0.90 and the root mean square error of prediction (RMSEP) was 0.45 and 0.07, respectively.

The study by Meng et al. (2021) investigated hyperspectral imaging technology with chemometric algorithms was examined. The CARS-MLR model was the best for predicting SSC and firmness, with R^2 values above 0.9 and 0.6 and RPD values above 3.7 and 1.8. Specifically, the values for SSC were (R^2 = 0.93, RMSEP = 0.57%, RPD = 3.73) and for firmness (R^2 = 0.69, RMSEP = 0.63 kg/cm^2, RPD = 1.81).

Canteri et al. (2019) studied use of infrared spectroscopy combined with multivariate analysis to evaluate the main components of cell walls of 29 plant species. It achieved excellent predictions ($R^2 \geq 0.9$ and RPD ≥ 3.0) for alcohol insoluble solids (AIS) and the content of different components, such as arabinose, glucose, non-cellulosic glucose, neutral sugars, methanol, and starch in AIS samples.

In another research (Louw, Theron 2010), Fourier transform near-infrared (FT-NIR) reflectance spectroscopy (800–2700 nm) was used to develop multivariate predictive models for evaluating total soluble content (TSS), total acidity (TA), sugar-acid ratio, firmness, and weight in three plum varieties. R^2 values between 0.817 and 0.959 and RMSEP 0.453–0.610% Brix were obtained for TSS, while, R^2 values 0.608–0.830 and RMSEP 0.110–0.194% malic acid were obtained for TA. The sugar-acid ratio reached R^2 values of 0.718–0.896 and RMSEP 0.608–1.590. Firmness had R^2 values of 0.623–0.791 and RMSEP 12.459–22.760 N, while weight had R^2 values of 0.577–0.817 and RMSEP 7.700–12.800 g. The 'Pioneer' and 'Laetitia' variety models had better predictive ability than the 'Angeleno' model for all evaluated parameters. Multivariate models had higher R^2 but also higher prediction errors for TSS, TA, and sugar-acid ratio.

Apricots and peaches. Several studies have confirmed the use of NIR spectroscopy for to evaluate of the quality of apricots and peaches (Bureau et al. 2010; Rong et al. 2020; Sun et al. 2021; Huang

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et al. 2022; Yang et al. 2022). Guan et al. (2022) used a SACMI NIR spectroscopy analyzer (800–2 600 nm) to develop a model to evaluate the internal quality of 'Shenzhou' peach variety. The correlation results were for SSC: R^2 = 0.79, P < 0.01, SEP = 0.47; for firmness: R^2 = 0.47, P < 0.01, SEP = 2.01; and for pH: R^2 = 0.40, P < 0.01, SEP = 0.14.

Özdemir et al. (2019) evaluated the quality of 'Hacıhaliloğlu' and 'Kabaaşı' apricots using spectrometers in the range of 12 000 to 4 000 cm^{-1} (NIR) and 4 000 to 650 cm^{-1} (MIR). Predictive models for SSC had Rp^2 between 0.827 and 0.913, RMSEP between 1.43 and 1.85, and RPD between 2.42 and 3.39. For TA, the monocultivar models did not give accurate results, but the multicultivar model was more accurate (Rp^2 = 0.701, RMSEP = 0.99, RPD = 1.84).

Quality analysis of apricot fruit was carried out using NIR (800–2500 nm) on intact fruit and MIR (4 000–650 cm^{-1}) on pulp samples. The results were acceptable for SSC using NIR and for SSC and TA using MIR (Bureau et al. 2012a).

In the study by Berardinelli et al. (2010) of the quality of apricots (variety 'Bora') was evaluated using FT-NIR reflectance spectroscopy in the range of 12 000 to 4 000 cm^{-1}. Apricot spectra were classified with an average success rate of 87% (range: 80% to 100%). Testing validation of PLS models showed R^2 values up to 0.620, 0.863, 0.842, and 0.369 for fruit firmness (FF), SSC, A, and TA, respectively.

For real-time measurements, the fruit was scanned on trees under field conditions. Optimization used an integration time of 30 ms and a wavelength range of 670–1 000 nm for SSC prediction, while a 20 ms integration time and the same wavelength range were ideal for pH and TA prediction due to the lowest RMSECV. The resulting models achieved R^2 and RMSEP values: 0.66 and 0.86 °Brix (SSC); 0.79 and 0.15 (pH); 0.71 and 1.91% (TA) (Posom et al. 2020).

NIR models on whole fruit achieved predictive errors of 9.2% (SSC) and 16.5% (TA). In the case of MIR models on pulp samples, the error decreased to 6.1% (SSC) and 8.6% (TA) (Bureau et al. 2012b).

Models were developed for individual apricot varieties and tested as global ones, combining various varieties. The accuracy of SSC prediction was RMSECV 0.67 to 1.1 °Brix with R values of 0.88 to 0.96. Fruit firmness was predicted with different accuracy depending on the variety, with RMSECV 6.2–13% (R values 0.85–0.92) for 'Kioto' and 'Harostar' varieties, but with insufficient accuracy (RMSECV = 24%) for the 'Bergarouge' variety. TA predictions had RMSECV from 0.79 to 2.61 g/100 mL and R values from 0.73 to 0.97 (Camps, Christen 2009).

The objective was to implement rapid and reliable methods for determining the optimal harvest time using a DA-meter and a NIR analyzer. Optimized curves showed high predictive ability for TA, SSC, and pH with R^2 in the range of 78.57–80.56. More work is needed to develop models for firmness (R^2 = 38.53), and further research is needed to better adapt data from penetrometers or other devices measuring pulp texture (Ciacciulli et al. 2018).

The study evaluated the use of Vis/NIR hyperspectral imaging (400 to 1000 nm) for predicting flesh firmness (FF) and SSC in apricots during storage (11 days). The PLS method achieved R^2 (test set) values up to 0.85 (RMSEP = 1.64 N) for FF and 0.72 (RMSEP = 0.51 °Brix) for SSC. For ANN, the best results were obtained for FF (R^2 = 0.85, RMSEP = 1.50 N) (Benelli et al. 2022).

In this study, a commercial Vis/NIR spectrometer was used to determine the soluble solids contents (SSC), dry matter concentration (DMC), and flesh firmness (FF) in varieties of peaches, apricots, and Japanese plums. Models, based on the second derivative of absorbance in the 729–975 nm spectral region, accurately predicted SSC and DMC (R^2_{CV} > 0.75), but not FF (R^2_{CV} < 0.75) (Scalisi, O'Connell 2021).

In another study, laser light backscatter imaging of was used to predict the quality of apricots during ripening. A high correlation was found between the features extracted from the images and the quality parameters of apricots, with the artificial neural networks (ANN) modelling giving better results than the partial least squares (PLSR) method. The highest R^2 values and the lowest RMSE of cross-validation were achieved by the ANN for firmness and total soluble solids (TSS), with R^2_{CV} = 0.974, RMSECV = 3.482 and R^2_{CV} = 0.963, RMSECV = 1.146 (Mozaffari et al. 2022).

Calibration methods have also been developed that relate physical parameters obtained by standard methods to spectral measurements in the range of 780 to 2 500 nm using PLS. For the maximum strength according to Magness-Taylor (MT), R^2 values of 0.82 (root mean square error of estimation (RMSEE) = 4.45) in calibration and 0.80 (RMSECV = 4.68) in validation were achieved for the apricot variety from multiple harvests (Buyukcan, Kavdir 2017).

The ATR-FTIR method was also tested for predicting the internal characteristics of peaches, such as sweetness and acidity. The best results were ob-

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tained for SSC and TA, with RMSECV ranging from 5.8 to 8.7% for SSC and from 5.9 to 8.0% for TA, depending on the samples (Bureau et al. 2013).

A total of five PLS models using NIR and MIR spectra were developed on 300 apricot samples and calibrated for total phenols (TPs), flavanols (FLs), carotenoids (TCs), and antioxidant capacity (AC). All models achieved high correlations, with coefficients greater than 0.95. Excellent results were recorded for TPs and FLs ($R\mathrm{p}^2$ = 0.99, RMSEP = 0.73 g/kg GAE, RPD = 12.0 and $R\mathrm{p}^2$ = 0.99, RMSEP = 0.95 g/kg GAE, RPD = 9.9 for MIR and NIR models respectively, $R\mathrm{p}^2$ = 0.99, RMSEP = 0.99 g/kg CAT, RPD = 8.5 and $R\mathrm{p}^2$ = 0.98, RMSEP = 1.10 g/kg CAT, RPD = 6.4 for MIR and NIR models respectively). MIR and NIR models for TCs showed solid prediction ($R\mathrm{p}^2$ = 0.98, RMSEP = 0.01 g/kg β-carotene, RPD = 6.5 and $R\mathrm{p}^2$ = 0.95, RMSEP = 0.01 g/kg β-carotene, RPD = 4.5 for MIR and NIR models respectively) (Amoriello et al. 2019).

Fruit firmness, soluble pectin content, and of methanol and succinate absorption in peaches were monitored with coefficients of determination R^2 of 0.80, 0.82, and 0.90 respectively, using PLS regression on spectra of wavelengths from 500 to 1 000 nm. Changes in the amount of pigments (especially chlorophyll) in the 500 to 560 nm and 630 to 690 nm regions were also used to construct models (Uwadaira et al. 2018).

Hyperspectral imaging was used to analyze light scattering from 'Red Haven' and 'Coral Star' peach varieties for to estimate fruit firmness, with an average coefficient of determination R^2 above 0.990 for a two-parameter Lorentzian function. The wavelength of 677 nm wavelength had the highest correlation with fruit firmness, with R^2 values of 0.77 and 0.58 for 'Red Haven' and 'Coral Star' respectively (Lu, Peng 2006).

A method combining hyperspectral imaging and machine learning was proposed to identify the bruising process in yellow peaches, with XGBoost model accuracies of 77.5%, 87.5%, and 90.0% for spectral, image, and combined data, respectively. To simplify the model, the CARS algorithm was used for wavelength selection from normalized spectral data, combined with image data, with an overall XGBoost model accuracy of 95.0% (Li et al. 2022).

Hyperspectral imaging for peach defects detection faces challenges due to fruit colour variability, similarity of defects and stems, and uneven light distribution on the surface. The implementation of a two-stage multivariate analysis process (Monte Carlo-Uninformative Variable Elimination and successful projections algorithm) in the spectral domain allowed the identification of artificial defects and the selection of discriminative wavelengths (DW). The resulting classification accuracy of 93.3% for 120 samples demonstrated the effectiveness of this method (Zhang et al. 2015).

Further investigation focused on the quantitative analysis of damage in yellow peaches using hyperspectral technology and mechanical parameters. The key features were the absorbed energy and the maximum contact force, as indicated by the R^2 values (0.83 and 0.90). The SNV-CARS-PLSR prediction model achieved optimal results for these measurements (Cozzolino et al. 2022).

Structured reflectance image spectrometry (SIRI) was used to detect early-stage fusarium infection. The method used of a multispectral SIRI system and seven wavelengths ranging from 690 nm to 810 nm. The application of a convolutional neural network (CNN) for image classification achieved a high detection success rate of 98.6%, with a 97.6% success rate for early infected peaches with difficult-to-detect symptoms (Sun et al. 2019).

In the recent research, hyperspectral reflectance spectrometry (400–1 000 nm) was used to evaluate and classify three peach diseases. The deep neural network model deep belief network (DBN) outperformed the partial least squares discriminant analysis model (PLSDA), achieving accuracies of 82.5%, 92.5%, and 100% for mild, moderate, and severe decay respectively. Model optimization of SPA-PLSDA from 494 to six features showed improved results and industrial applicability (Sun et al. 2018b).

A hyperspectral imaging system with a mobile inspection platform enables comprehensive imaging of the peach for the identification of diseases caused by *Rhizopus stolonifera*. Three monochromatic images (709, 807, and 874 nm) were selected using statistical methods and an image segmentation algorithm to locate infected areas. Peaches were classified based on the degree of affliction (healthy, slightly afflicted, moderately afflicted, and severely afflicted) with detection accuracies of 95%, 66.29%, 100%, and 100% for each category respectively. When reduced to two categories (healthy and rotting), the classification achieved 100% accuracy. This system provides effective identification of afflicted areas and is suitable for online monitoring (Sun et al. 2018a).

Remote sensing can reduce the cost of pest monitoring in orchards. An assessment of mite damage de-

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tection in peach trees identified eight spectral regions on leaves and two regions (blue and red) that correlated with mite damage. These results were validated by calculating normalized difference indices of red and blue radiation from six multispectral aerial images, with a correlation between index values and mite damage (R^2 = 0.47) (Luedeling et al. 2009).

Sweet and sour cherries. Near-Infrared spectrometry has demonstrated the ability to effectively predict sweet cherry and sour cherry attributes such as sugar content, acidity, firmness, and colour, (Overbeck et al. 2017; Wang et al. 2018; Li et al. 2018b; Chełpiński et al. 2019; Fodor 2022).

In this study, a Cherry-Meter device measuring the index of absorbance difference (IAD) was used, and its reliability as a maturity indicator was verified by correlating it with attributes such as peel colour intensity, anthocyanin content, and soluble solids content (SSC) in the fruit (Nagpala et al. 2017).

Eleven hyperspectral images of 550 fruits in the range of 874–1 734 nm were obtained and compared with the SSC and pH values obtained by standard methods. The genetic algorithm multiple linear regression (GA-MLR) method was chosen as the final modelling technique with a ratio of the standard deviation of the prediction set to the standard deviation of the prediction error of 2.7 for SSC and 2.4 for pH. Linear discriminant analysis achieved a correct classification of 96.4% (Li et al. 2018b).

The study also developed NIR spectroscopy models for a handheld device in the spectral range of 729–975 nm, which were found to be accurate and robust for sweet cherries. The determination coefficients (R^2) for model calibration were 0.922–0.946 for SSC and 0.910–0.933 for dry matter content (DMC), with calibration errors of 0.612–0.792 for SSC and 0.687–0.911% for DMC. External validation showed the models to be reliable for 'Chelan' and 'Bing' varieties, with R^2 values of 0.726–0.891 for SSC and 0.670–0.725 for DMC (Escribano et al. 2017).

Fourier transform near-infrared spectroscopy (FT-NIR) was used to analyze of the ripeness of sweet and sour cherries, with reference values of titratable acidity (A), soluble solids content (SSC), total anthocyanin content (TA), and a calculated ripeness index (SSC/A = MI). Correlations were validated by sevenfold cross-validation and test validation (Fodor 2022).

The study demonstrates the application of sensor technology to non-destructively determine the optimal harvest date (OHD) of sweet cherries. Changes in colour, quantified by NDVI (normalized differential vegetation index) and NAI (normalized anthocyanin index), were used to categorize cherry ripening. The OHD model correlated with the moment when the NDVI exceeded zero and the first derivative of the NAI asymptotically approached zero (Overbeck et al. 2017).

Soft independent modelling of class analogies (SIMCA) was used to detect differences in fruit quality in modified atmosphere (MAP) as a function of washing, with prediction error rates between 0 and 0.5 (Szabo et al. 2023).

The use of visible and near-infrared (Vis-NIR) reflectance spectroscopy to identify damage of sweet cherries achieved a classification accuracy of 93.3% when using the LS-SVM model (Shao et al. 2019).

A spectrometer (800–2 600 nm) evaluated different types of sweet cherries according to the pit content, with the binary model achieving an overall accuracy of 98%. Accuracy dropped to 96% when limited to four significant features and was lowest when separating fragment classes (Liang et al. 2017).

Small fruits

Blueberries. NIR spectrometry has been studied as a tool to evaluate the quality of blueberries, especially sugar content, acidity, and firmness (Leiva-Valenzuela et al. 2013; Jiang, Takeda 2016; Bai et al. 2022).

Bai et al. (2022) focused on its use to estimate the soluble solids content in blueberries, using a combined model calibration strategy. The use of global modelling methods, dynamic orthogonalization projection (DOP) and slope/bias correction (SBC), reduced the RMSEP values of the model by up to 55.9% for seasonal variables ('Bluecrop'-2014), 45.8% for variety variables (M2-2015), and 9.3% for variety variables (Duke 2015).

Leiva-Valenzuela et al. (2013) used hyperspectral imaging technique to predict blueberry firmness (R^2 = 0.87) and soluble solids content (R^2 = 0.79). A pushbroom hyperspectral imaging system was used, to acquire spectra in the 500–1 000 nm range.

According to Goisser et al. (2021), cross-validation models achieved values of up to 0.94 for evaluating moisture content and up to 0.95 when evaluating sugar content in blueberries. Three different commercial food scanners were used for measurement.

Jiang and Takeda (2016) conducted experiments on blueberry samples (varieties 'Camellia', 'Rebel', 'Star', 'Bluecrop', 'Jersey', and 'Liberty') for hyperspectral

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image analysis, firmness measurement, and human evaluation. They achieved accuracy rates of over 94%, 92%, and 96% on the training set, independent test set, and combined set, respectively.

Huang et al. (2020b) investigated the potential of hyperspectral imaging for differentiating early disease in blueberries. The effective spectral range (400–1 000 nm) combined with an autoscaling method achieved recognition rates of 100% for healthy blueberries and 99% for blueberries with early disease.

Sinelli et al. (2011) utilized NIR spectra to monitor changes caused by osmotic treatments. Spectral differences reflected the major molecular changes associated with osmotic dehydration, and two-dimensional correlation analysis of spectral data was also performed to examine the variation of major components (sugars and water).

Raspberries. Detection of quality and health of raspberries can be significantly improved thanks to advanced technologies. NIR spectrometry can effectively predict even phenolic and carotenoid content (Toledo-Martín et al. 2018).

Research by Rodríguez-Pulido et al. (2017) showed that the partial least squares regression method, together with image analysis data, enabled the prediction of raspberry chemical properties with coefficients of determination (R^2) up to 0.75. Colour data provided the most accurate predictions for total anthocyanins.

In this study, three genotypes of *Rubus idaeus* were subjected to biotic stress caused by the pathogen *Phytophthora rubi* and the pest *Otiorhynchus sulcatus*, as well as abiotic stress caused by limited soil water availability. Significant differences in plant biological characteristics and canopy reflectance spectrum were observed among genotypes and stress conditions. The most notable differences were observed when monitoring the reflectance ratio at wavelengths of 469 and 523 nm, where a significant interaction between genotypes and stress conditions was recorded (Williams et al. 2023).

Strawberries. NIR spectrometry offers advantages in the analysis of rapidly deteriorating fruit, such as strawberries. Sugar content, acidity, and firmness (Mancini et al. 2020; Agulheiro-Santos et al. 2022) are key parameters for rapid assessment. Fourier transform NIR spectrophotometry (FT-NIR mod. Nicolet iS10, Thermo, Waltham, MA, USA) provides high correlation values R^2 up to 0.87 and standard prediction errors 0.84 °Brix when predicting the content of soluble solids content (SSC) in strawberries (Mancini et al. 2023). The partial least squares (PLS) method for predicting SSC content was found to be the most effective and was also robust even for predicting fruit firmness (Mancini et al. 2020).

Seki et al. (2023) developed a method to visualize sugar distribution in the flesh of white strawberries using hyperspectral imaging in the NIR spectrum (913–2 166 nm), achieving RMSEP and R^2 values of 0.576 and 0.841.

Włodarska et al. (2019) used NIR spectroscopy for the analysis of strawberries and juices and achieved high precision with R^2 values of up to 0.9277, 0.5755, and 0.8207 for the calibration, validation, and prediction model when predicting SSC. For prediction of TPC, R^2 = 0.834 and RMSEP = 130.8 mg GA/L were obtained using NIR spectra of strawberries, or R^2 = 0.844 and RMSEP = 126.7 mg GA/L using UV-VIS-NIR spectra of juices.

In the spectroscopic and physicochemical analysis of strawberries of the 'Victory' variety, predictive models for titratable acidity, colour, and texture achieved low precision. On the contrary, NIR quantitative predictive analysis of TSS achieved high accuracy when applying spectral preprocessing with determination coefficients of 0.9277, 0.5755, and 0.8207 for the calibration, validation, and prediction model, using a seven-factor PLS analysis (Agulheiro-Santos et al. 2022).

Another part of the study, focused on the classification of strawberries according to storage time, used the Support Vector Machine (SVM) method with multiplicative scatter correction, achieving 100% accuracy. Then, a partial least squares regression model (PLS) was developed to predict the storage time of strawberries, with a prediction determination coefficient (R^2) of 0.9999 and prediction error (RMSEP) of 0.0721. Ten key wavelengths, obtained by eliminating uninformative variables, were used in the SVM model, which achieved R^2 of 0.9943 and RMSEP of 1.3213 (Wenga et al. 2023).

In another study, aquaphotomics and NIR spectroscopy were used to monitor changes in strawberries during chilled storage in a supercooled fridge (SCF) and a control fridge (CF). Aquaphotomic analysis showed that NIR spectra effectively reflected changes in strawberry condition of during storage and allowed predicting of storage time (Muncan et al. 2022).

Yet another study used visible and NIR spectroscopy (Vis/NIR) for rapid evaluation of storage time and prediction of post-harvest quality of strawberries. The PLS-DA method achieved classification accu-

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racy of 93.3%–97.4% depending on the speed of fruit movement (0.05, 0.10, and 0.15 m/s) based on selected wavelengths obtained using the competitive adaptive reweighted sampling (CARS) method. For predicting the soluble solids content (SSC) in strawberries, the PLS method with CARS achieved a determination coefficient (R^2) of 0.733, root mean square error of prediction (RMSEP) of 0.699 °Brix, and residual prediction deviation (RPD) value of 1.96 at a fruit movement speed of 0.10 m/s (Shen et al. 2018).

In the study by Yeh et al. (2016), hyperspectral and multispectral imaging techniques were used to diagnose the stages of anthracnose infection in strawberry leaves. Three methods of hyperspectral imaging analysis, i.e., spectral angle mapper (SAM), stepwise discriminant analysis (SDA), and independently developed correlation method (CM), achieved average accuracies over 80% in classifying two stages (healthy and symptomatic). The SDA method achieved an average accuracy of 93% for a two-stage classification. For a three-stage classification, the 551, 706, 750, and 914 nm wavelengths achieved 80% accuracy using the PLS regression method for standard wavelength selection.

Detection of grey mold on strawberry leaves was performed using hyperspectral images and the development of three machine learning models: extreme learning machine (ELM), support vector machine (SVM), and K-nearest neighbour (KNN). Models based on optimized wavelengths (OWs) and vegetation indices (VIs) achieved classification accuracies of up to 93.33%. Although the model using texture features (TFs) showed lower performance, the combination of different features (OWs, VIs, TFs) significantly improved the accuracy of gray mold detection in strawberries, allowing accurate identification of infected leaves at the early stages (Wu et al. 2023).

Another study examined the application of near-infrared spectroscopy on berry fruit extracts for predicting total phenol content (TPC) and antioxidant activity (AoA indicators), such as DPPH radical quenching, Briggs-Rauscher reaction inhibition time (IT), and relative antioxidant capacity (rac) of the Partial least squares (PLS) models were developed to verify the relationship between NIR spectra of berry fruit and TPC and AoA. The determination coefficients (R^2) exceeded 0.84 and residual prediction deviation (RPD) values ranged from 1.8 to 3.1, confirming the sufficient accuracy of the validated PLS models (Kljusurić et al. 2016).

Grape wine. The use of NIR spectrometry to assess the maturity, sugar content, and acidity of grapes has been the subject of several studies (Daniels et al. 2019; Ping et al. 2023). Spectrometry is also used to evaluate the quality and composition of grapes and wines (Guidetti et al. 2010; Poblete-Echeverría et al. 2020; van Wyngaard et al. 2021) and even to identify and authenticate wines (Fernández et al. 2007; Geană et al. 2019; Parpinello et al. 2019).

Poblete-Echeverría et al. (2020) introduced NIR spectroscopy and artificial neural networks (ANN) as an alternative to traditional methods (especially partial least squares - PLS) for evaluating the quality of table wine. ANN models based on NIR data agreed well with the content of total soluble solids (TSS), titratable acidity (TA), and TSS/TA ratio.

Ping et al. (2023) applied the method of visible near-infrared spectral (Vis-NIR) technology method for rapid and non-destructive detection of changes in the qualitative parameters of grapes during maturation. The SSC model obtained coefficients of determination for the calibration (R^2cal = 0.97) and prediction (R^2pre = 0.93) set, RMSEC and RMSEP were 0.62 and 1.27, and RPD 4.09. For TA, R^2cal, R^2pre, RMSEC, RMSEP, and RPD were 0.97, 0.94, 0.88, 1.96, and 4.55.

Daniels et al. (2019) evaluated the possibility of determining the main maturity parameters of table grapes on intact samples using FT-NIR spectroscopy and contactless measurement. For the parameters TSS, TA, TSS/TA, pH, and alternative parameter for determining the palatability (BrimA), calculated as TSS-k × TA, latent variables (LVs) were 21, 23, 5, 7, and 24, R^2p = 0.71, 0.33, 0.57, 0.28, and 0.77, and RMSEP = 1.52, 1.09, 7.83, 0.14, and 1.80.

Basile et al. (2022) developed multivariate models using ANN and PLS regressions and obtained good predictions for TSS and firmness (R^2 0.82 and 0.72). Qualitative models were obtained for hardness and chewiness (R^2 0.50 and 0.53). However, no satisfactory calibration model was obtained for cohesiveness.

Goisser et al. (2021) achieved cross-validation values (R^2) up to 0.92 for dry matter content and up to 0.95 for sugar content in table grapes, using three commercially available food scanners: SCiOTM, F-750, and H-100F.

Comparison of results obtained using NIR spectrometry with traditional analytical methods. According to a comparison made by Workman and Weyer (2012), NIR spectrometry appears to be a fast and accurate analytical tool that eliminates the need for complex sample preparation and achieves re-

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sults comparable to traditional methods. The study by Zhang et al. (2019) confirmed this fact and highlighted the advantages of NIR spectrometry in the context of increasing pressure for rapid and efficient fruit quality control. Slaughter and Abbott (2004) and Butz et al. (2005) also pointed out the growing importance of NIR spectrometry in the sphere of fruit quality control in response to the increasing demand for high quality fruit. Research by Scalisi et al. (2021) also showed that NIR spectrometry provides fast and accurate results that can help improve fruit quality control. The study by Amoriello et al. (2019) also demonstrated the efficiency of NIR spectrometry in determining the antioxidants content of in fruit, which is a key indicator of its nutritional value.

DISCUSSION

Evaluation of current research on the use of NIR spectrometry on temperate fruit. NIR spectrometry is emerging as an effective tool for evaluating the quality, maturity, and other parameters of temperate fruit. Li et al. (2018a) demonstrated the use of this technology to identify apple varieties using specific spectral characteristics. Daniels et al. (2019) suggested its effectiveness in determining sugar and acidity in grape wine, while Mozaffari et al. (2022) confirmed its ability to evaluate the ripeness of apricots.

The main advantage of NIR spectrometry is its speed and non-invasiveness, which provides accurate and reliable results. However, its accuracy depends on the calibration of the instrument and the quality of the reference data, as suggested by Nicolaï et al. (2007), Zhang et al. (2019), Bureau et al. (2013), Jiang et al. (2022), Marečkova et al. (2022). This suggests the need for further research to optimize and standardize this method.

From the analysis of the current research, it is clear that there is a need to focus on the calibration and validation of the models to achieve accurate results (Louw et al. 2010; Jiang et al. 2022; Hao et al. 2023) is apparent. We suggested that future studies should include more types of fruit to further expand the applications of NIR spectrometry.

Compared with traditional analytical methods, NIR spectrometry has proven to be an effective alternative for rapid and noninvasive evaluation of fruit (Li et al. 2018b), and even genetically modified organisms (Sohn et al. 2021). However, it is important to recognize that the accuracy and reliability of this method may be affected by the variability of fruit samples, instrument calibration, and the influence of the external environment. These aspects are further areas for future research.

Li et al. (2018a) demonstrated its usefulness for fruit variety identification, and Li et al. (2018b) provided a comparison with traditional analytical methods for cherries evaluation, noting the comparable accuracy of both methods.

However, there are limitations and challenges associated with the use of NIR spectrometry on temperate fruit, such as the variability in fruit properties, the need for adequate instrument calibration, and the consideration of external influences such as environment and storage conditions. Future research should address these issues and focus on improving the methods and technologies used in NIR spectrometry for the temperate fruit assessment.

Identifying trends, limitations, and opportunities for further development in this field. Research on NIR spectrometry as applied to temperate fruit reveals the considerable potential of this technique and its possible limitations. Important trends in the field, including the growing interest in automation and rapid analysis, were highlighted in the studies by Bureau et al. (2012a, 2012b) and Ali and Hashim (2022). However, limitations related to the variability of fruit characteristics, physical interferences, and the need for instrument calibration are of considerable importance, as shown in the study by Mishra et al. (2021).

Opportunities for further development include improving sensors and detectors, using advanced chemometric methods, and integrating with other technologies such as image analysis. These opportunities were illustrated in the studies by Rodríguez-Pulido et al. (2017), Li et al. (2018b) and Li et al. (2022), which explored the combination of NIR spectrometry with image analysis and hyperspectral imaging for better fruit classification.

The increasing use of advanced chemometric methods to analyze NIR spectrometry data was identified as another significant trend, as shown in the studies by Lin and Ying (2009) and Vilvert et al. (2023). Limitations associated with variability in the physical properties of fruit and measurement geometry were evaluated in Buyukcan and Kavdir (2017).

From the identified trends, limitations, and opportunities for further development, it follows that future research should aim to develop innovative ap-

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proaches and techniques for efficient and reliable fruit assessment using NIR spectrometry.

Recommendations for future research and applications of NIR spectrometry in fruit. Standardization and validation of methods are key to the successful application of NIR spectrometry, verifying its accuracy and reliability (Hao et al. 2023; Wu et al. 2023). Standardized procedures for measurement and analysis ensure consistent results and comparability between studies. Further research should aim to optimize methods and models for NIR spectrometry (Cadet et al. 2019; Weijie 2021). Given the importance of data analysis in NIR spectrometry, the development of chemometric methods for spectral data should continue (Meng et al. 2021; Yan et al. 2023).

Integration of NIR spectrometry with technologies such as image analysis, multispectral imaging, artificial intelligence, or robotics could provide a comprehensive solution (Luedeling et al. 2009; Yeh et al. 2016; Cadet et al. 2019; Sun et al. 2019; Pandiselvam et al. 2022).

Efforts to develop portable and miniaturized instruments are important for rapid fruit quality measurements (Pissard et al. 2021; Beć et al. 2022; Yan et al.2023; Minas et al. 2023; Kalopesa et al. 2023). Further development should aim at methods that allow the examination of the internal structure of fruit (Guan et al. 2022; Yan et al. 2023).

It is also important to expand the application of NIR spectrometry to the industrial level is also important (Kumaravelu, Gopal 2015; Qu et al. 2015; Patel et al. 2016; Daniels et al. 2019; Grassi, Casiraghi 2022; Tsuchikawa et al. 2022).

Future research and applications of NIR spectrometry to fruit should include expansion of applications, integration with other technologies, development of portable and miniaturized instruments, and standardization and validation of methods. These steps could contribute to the further development and utilization of NIR spectrometry in fruit evaluation.

CONCLUSION

Final recommendations. Further research should focus on optimizing methods and calibrations to achieve greater accuracy and reliability of analytical results (Jiang et al. 2022; Marečkova et al. 2022). The use of advanced chemometric methods and machine learning holds promise for improving the accuracy and reliability of predictive analysis results and identifying new fruit species (Kumaravelu, Gopal 2015; Poblete-Echeverría et al. 2020; Meng et al. 2021; Kalopesa et al. 2023; Vilvert et al. 2023). Future research should focus on optimizing methods and calibrations of NIR spectrometry to achieve even more accurate results (Hao et al. 2023; Wu et al. 2023).

The development of portable and mobile NIR spectrometers will enable their use directly on farms, in stores, or in fruit distribution centers. This will allow for quick and practical quality and ripeness checks on-site (Aline et al. 2023; Saeys 2023).

Summary of the main findings and results of the review. NIR spectrometry has proven to be an effective technique for the evaluation of temperate fruit, providing information about chemical composition, ripeness, and quality simultaneously, providing comprehensive information (Rodríguez-Pulido et al. 2017; Agulheiro-Santos et al. 2022; Mozzaffari et al. 2022; Kalopesa et al. 2023) without destroying the fruit, thus speeding up the evaluation process (Li et al. 2018b). Research confirms its reliability and accuracy compared to traditional analytical methods (Li et al. 2018b). Its potential for process automation and efficiency improvement in fruit farming is also evident (El-Mesery et al. 2019; Saeys 2023).

In the context of future research, it is important to continue developing calibrations and methodologies that increase the accuracy and reliability of analyses (Wu, Sun 2013; Huang et al. 2020a; Hasanzadeh et al. 2022).

The development of new technologies and devices is also an important aspect of further research (Yu et al. 2016; Nagpala et al. 2017; Sohn et al. 2021).

Future research should aim to develop advanced sensors, detectors, and light sources that would improve sensitivity, resolution, and measurement stability. Although NIR spectrometry provides valuable information for the evaluation of temperate fruit, there is still room for further research and development.

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