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Real-time moisture monitoring of edible coated apple chips during hot air drying using miniature NIR spectroscopy and chemometrics

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ABSTRACT

Fruits and vegetable powders are gaining attention due to their flavor, color, high nutritional content, and consumers' demand for compact and lightweight foods. This study was undertaken to explore their commercial applications as an edible coating onto sliced apples to incorporate various functional and nutritional characteristics to apple chips. The subsequent aim of this work was to investigate miniature NIR spectroscopy as a tool to rapidly monitor and develop a predictive model for the drying of edible coating on these apple slices. The apple slices coated with selected fruit powders were dried and compared with uncoated samples. NIR spectra were collected at different drying times, and multivariate calibration models were developed using partial least-squares regression (PLSR) with raw and various pre-treated spectra. Instead of selecting different sets of feature wavelengths for coated and uncoated apple slices, a set of 7 key wavelengths was selected for convenient application to monitor moisture content during drying of apples with or without edible coatings. The results showed that the miniature NIR spectroscopy was able to monitor the drying process and discriminate between the coated and uncoated apple slices and drying times, primarily by the differences in sugar and water absorption bands.

1. Introduction

Fruits and vegetables are an essential part of a healthy lifestyle, and their regular consumption has been reported to have various health-protective effects (Cui et al., 2019; He, Nowson, & MacGregor, 2006; Vainio & Weiderpass, 2006). This is attributed to a high content of fibers, vitamins, minerals, and phytochemicals, such as polyphenols, flavonoids, carotenoids, anthocyanins, etc., for their strong antioxidant activity (Cui et al., 2019). However, fresh fruits and vegetables are highly perishable commodities, due to their high moisture content, often above 85% (w.b.), and metabolic activities, and thus deteriorate over a short period if improperly handled (Moβhammer, Stintzing, & Carle, 2006). Therefore, processing fruits into a value-added product is often an effective strategy for increasing the shelf life, enhancing the nutritional content, reduce post-harvest loss, and promoting fruit consumption. Fruit and vegetable powders are an important product produced by drying the fresh produce, which retains the unique sensorial characteristics and nutritional value of the starting material. There is a growing demand for dried snack foods like apple chips, which provide convenience, taste, nutritional, and other health benefits (Zandstra, De Graaf, & Van Staveren, 2001). Noticeably, many snack foods are coated with powdered seasonings to enhance their flavor and increase product variety. Recently, researchers have attempted to use different coatings to improve nutritional content, provide anticaking properties, and apply as antimicrobial agents to fresh products to enhance their shelf life (Amefia, Abu-Ali, & Barringer, 2006; Campos, Gerschenson, & Flores, 2011; Limjaroen, Ryser, Lockhart, & Harte, 2003). Nevertheless, no reports have documented the use of fruit and vegetable powders as a coating material for apples before hot air drying to increase the nutritional value and color attractiveness of dried apple chips.

Drying removes the water needed for bacteria, yeasts, and molds to multiply. If adequately dried and properly stored, dehydrated foods are shelf-stable. Therefore, it is important to accurately monitor the moisture content (MC) to ensure a safe product in the drying process. In general, the drying kinetics of foods are evaluated by measuring the weight loss during drying over a period. However, analyzing MC by conventional methods like oven drying and vacuum drying is often time-consuming, destructive, and requires a large amount of sample

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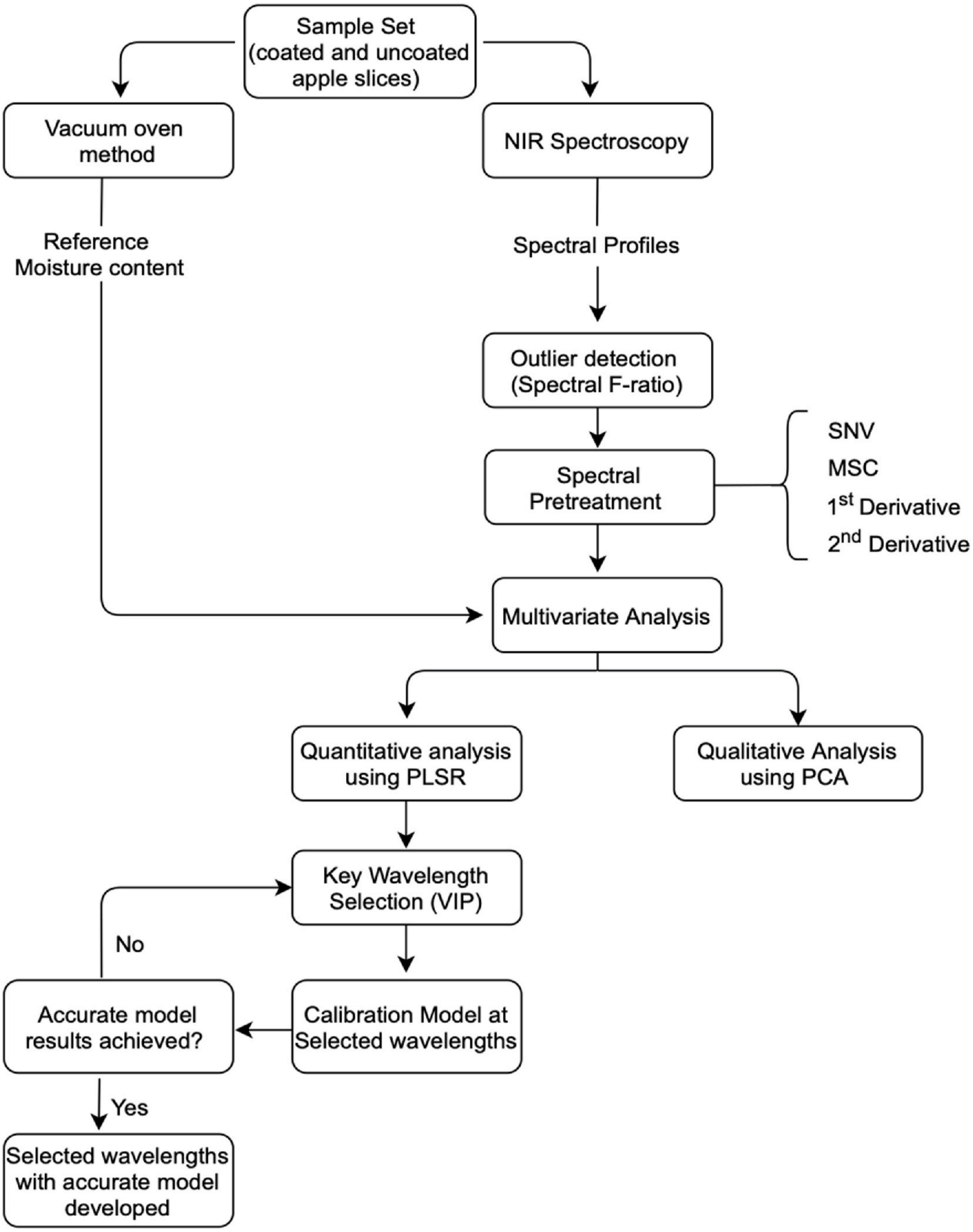

Fig. 1. Step by step procedure for developing calibration models and key wavelength selection for monitoring moisture content during drying.

preparation. Recently, some spectroscopic techniques have been gaining attention as they are non-destructive, fast, cost-effective, and allow for high throughput (Kamruzzaman, Elmasry, Sun, & Allen, 2012). Compared with other spectroscopic techniques, NIR (Near-Infrared) spectroscopy has emerged as a more feasible option in the food industry, incorporating advantages of real-time, high precision, and non-destructivity.

In the spectra, the information about MC and other indicators such as sugar, protein, fat, etc., is mainly derived from the absorption bands in the NIR region. These absorption bands are generated from fundamental vibrations by two processes, i.e., overtones and combinations (Grassi & Alamprese, 2018). However, since NIR spectra generally consist of overlapping vibrational bands (Hernandez-Cardoso, 2020), chemometrics is usually used to extract meaningful information from the NIR spectra. Several researchers have utilized NIR Spectroscopy to determine moisture, sugar, protein, and fat in various food products such as guava and passionfruit (Alamar, Caramês, Poppi, & Pallone, 2016), pear (Mishra, Woltering, Brouwer, & Hogeveen-van Echtelt, 2021), apples (Jannok, Kamitani, & Kawano, 2014), bread (Nallan Chakravartula, Cevoli, Balestra, Fabbri, & Rosa, 2019), breakfast cereals (Aykas, Ball, Menevseoglu, & Rodriguez-Saona, 2020), and meat (Isaksson, Nilsen, Tøgersen, Hammond, & Hildrum, 1996; Kamruzzaman, Makino, & Oshita, 2016), among others. Furthermore, various researchers have extended NIR applications for evaluating and monitoring the drying process of different food products (Collell, Gou, Arnau, & Comaposada, 2011; Sinelli, Casiraghi, Barzaghi, Brambilla, & Giovanelli, 2011).

In recent developments, due to its considerably lower cost, portable and miniature NIR spectrometers are being used commonly to analyze the properties of various food products. The performance of these miniature instruments sometimes varies due to technical limitations, such as type of energy source, detector, resolution, sampling accessories, and energy intensity used within the system (Soriano-Disla, Janik, Allen, & McLaughlin, 2017). However, researchers have found that miniature NIR spectrometers can predict various properties of food with good accuracy at a cheaper cost (Bobasa, Netzel, Cozzolino, Phan, & Sultanbawa, 2021; Lin et al., 2019; Cruz-Tirado, Lucimar da Silva; Medeiros, & Barbin, 2021). Therefore, portable, miniature NIR spectrometers appear to be a viable solution for providing rapid and cost-effective moisture content analysis of apples.

As mentioned earlier, it is important to carry out moisture content analysis using an accurate and robust method as it influences the physical appearance, texture, taste, and shelf-life of dried food products. To our knowledge, no study is available to monitor the hot air-drying process using miniature NIR with multivariate analysis regarding edible coating applied onto apple slices. Therefore, the overall objective of the present study was to use a miniature NIR spectroscopy as a tool to evaluate a hot air drying process and develop a multivariate calibration model for real-time monitoring of MC during drying of coated (C-A) and uncoated (UC-A) apple slices in a pilot-scale hot air dryer. In this context, the specific objectives of the present study were (a) to evaluate the accuracy, robustness, and reliability of the spectral response obtained from the miniature NIR sensor for monitoring the moisture content during drying of C-A and UC-A slices in a hot air dryer (b) identify important feature wavelengths (WL) by multivariate data analysis for real-time moisture monitoring of apple drying process, and (c) to develop and optimize multivariate calibration models using the selected feature WL to apply the model to predict moisture content.

2. Materials and methods

The key steps for monitoring MC during drying using NIR spectral analysis are outlined in Fig. 1 and explained in detail in the following sections.

2.1. Sample preparation

Apples (Gala var.) were procured from a local market in Urbana, Illinois. Fresh apples were washed and then cut into 3 mm thick slices using a laboratory slicer. Fruit powder [cranberry (MC = 3.5% w.b.), FutureCeuticals, Inc. Momence, IL.] and acetylated monoglyceride (AMG) (DuPont Inc., Wilmington, DE) were used to prepare the coating solution.

2.2. Formulation and application of coating solution

The coating solutions were prepared by dispersing 1% w/w AMG in distilled water. This dispersion was heated up to 30 °C for 15 min while continuously stirred on a hot plate with a magnetic stirrer. The solution was subsequently cooled to room temperature (25 °C) followed by the addition of 10% w/w cranberry powder. This solution was then homogenized at 7000 rpm for 5 min with a high shear homogenizer. The coating solution was then applied by dipping apple slices individually in the coating solutions for 5 min at room temperature (25 ± 2 °C).

2.3. Hot air drying

In this study, a custom-designed single-channel laboratory hot air dryer consisting of six sections was used for drying apple slices. These six sections included a dehumidifier (Frigidaire, Charlotte, North Carolina, USA) to lower the dryer inlet air humidity for low humidity drying; a centrifugal air blower (Ebmpapst, Farmington, Connecticut, USA) to draw air into the dryer system; an ultrasonic humidifier chamber, which included a 20-mm ultrasonic transducer (HM 2412, Honda Inc., Japan) installed in a custom-made pan to increase air humidity for high humidity drying; two Omegaflux heaters (Omega Engineering, Stamford, Connecticut, USA) to provide thermal energy; a drying section including a square or round sample holder (36 inch × 5 inch × 5 inch) and a temperature-humidity sensor (Omega Engineering, Stamford, Connecticut, USA) to monitor the humidity and temperature of intake air, and a load cell to monitor sample weight changes. A Fantech IR series iris damper (System air, Sweden) was mounted to the fan to control the air velocity. This equipment has been fully described previously (Kahraman, Malvandi, Vargas, & Feng, 2021). The dryer was operated at an air velocity of 2 m/s, parallel to the drying surface of the apple slices (3 mm thick), and 60 °C dry bulb temperature. Samples were dried until equilibrium (no weight change) was reached.

2.4. Acquisition of NIR spectra

NIR Spectra were collected by a miniature NIR Spectrometer (model DLP2010NIR, Texas Instruments, Dallas, Texas, United States) with 228 spectral bands optimized between 900 and 1700 nm. Scans were performed 32 times for each sample (total measurement time for each same was 7.74s). For this instrument, the signal was captured using a DLP NIRscan Nano GUI (v2.1.0) software, and subsequently, the data were processed using MATLAB (Version R2020b, The Mathworks, Natick, Massachusetts, USA). In total, 102 samples (54 for coated and 48 for uncoated) were used for investigation. After associating the spectra with the reference moisture content values, data were manually divided into calibration (~67%, 68 samples) and validation sets (~33%, 34 samples).

2.5. Measurement of moisture content and drying rate

After the acquisition of spectra, reference moisture content (MC) of each sample for coated and uncoated apple slice at different drying stages were determined using the vacuum oven method (24 h at 70 °C, 3.33 kPA) (AOAC,1990). Samples before and after vacuum drying were weighed. The average moisture content was expressed on a dry basis (d. b.)

2.6. Chemometrics and data analysis

2.6.1. Outlier detection

Outliers are known to have a strong influence on the estimation of model performance. Therefore, to achieve a greater calibration accuracy, outliers were identified and removed from the calibration set. The American Society of Testing Standards (ASTM) recommended that various outlier diagnostic tests can be used for spectral data analysis. In this study, outliers were identified by comparing moisture content residuals (y residuals) with the root mean square error of cross-validation (RMSECV). Using this criterion, a sample is considered an outlier and eliminated from the dataset if the difference between its actual and predicted values exceeds two times RMSECV (Valderrama, Braga, & Poppi, 2007). However, no outliers were detected during the calibration process using this criterion.

2.6.2. Exploratory analysis using principal component analysis (PCA)

PCA was applied to reduce the high dimensionality of the spectral data (Daszykowski & Walczak, 2006), check the pattern of moisture loss during drying, and monitor the drying process qualitatively. PCA finds fewer factors or components than original variables through orthogonal transformation (Cozzolino, Power, & Chapman, 2019). After outlier elimination, PCA was applied to the spectral data on both coated (54 × 228) and uncoated (48 × 228) apple slices to obtain an overview of variation among samples with respect to drying time. The data matrix was mean-centered before PCA, and cumulative percent explained variance was used to choose the optimal number of principal components (PCs). The explained variance by a PC is the ratio (expressed as a percentage) between the variance of that PC and the total variance.

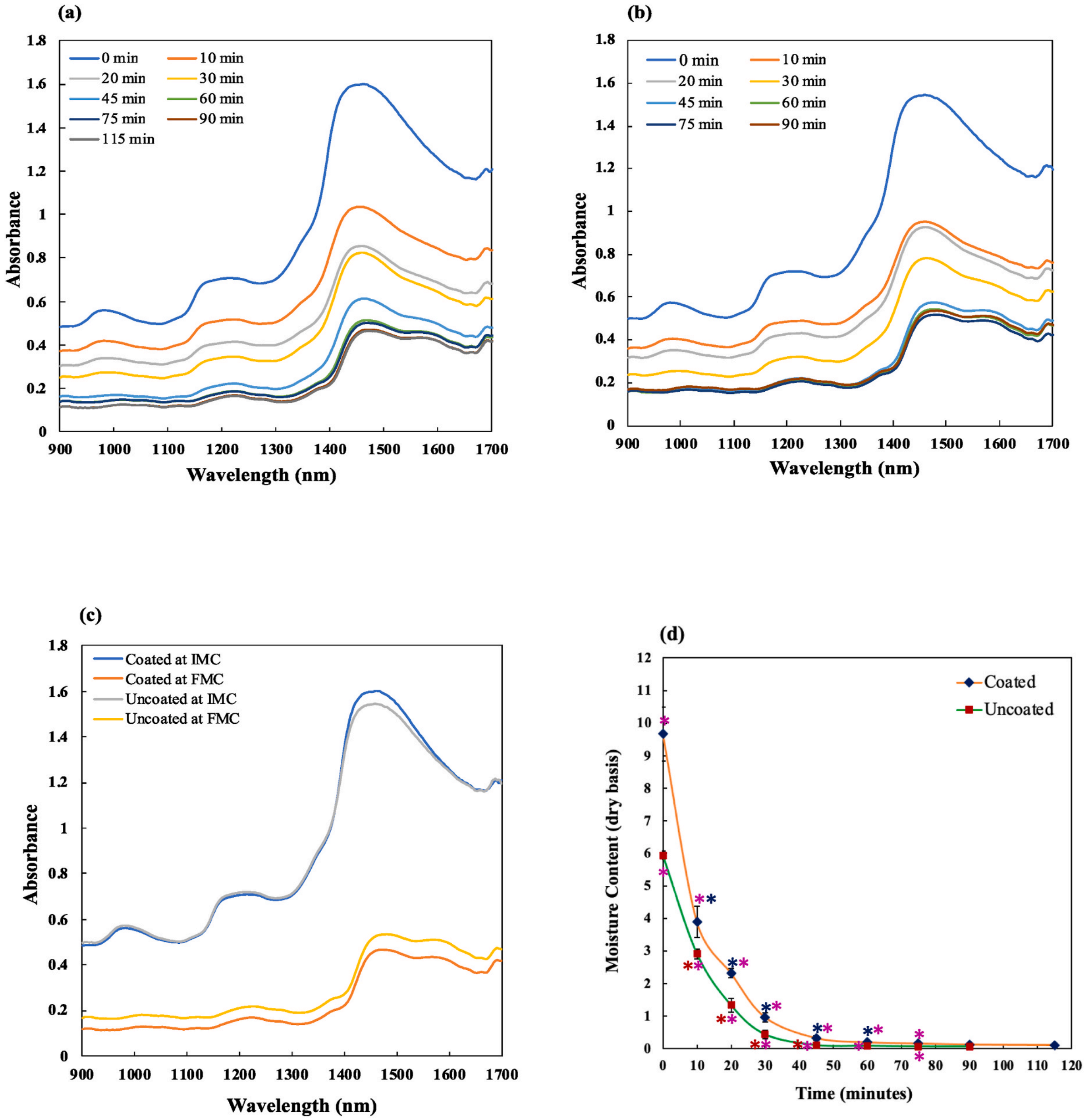

Fig. 2. Representative NIR spectrum of (a) coated (b) uncoated apple slices, (c) coated and uncoated apple slices at their initial and final moisture content. (d) Moisture content (% d.b.) for coated and uncoated apple slices against the drying time for temperature of 60 °C and air velocity 2 m/s (Blue asterick marks the significant differences between moisture content of coated samples at different time intervals; Red asterick marks the significant differences between moisture content of uncoated samples at different time intervals; Pink asterick marks the significant differences between moisture content of coated and uncoated samples at the same time, all with a significance level of $p < 0.05$.). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

2.6.3. Spectra pre-processing

Some interference factors exist in the collected NIR spectra, such as sample morphology, scattered and stray light interference, instrumental noise, etc. To reduce the influence of these interference factors, the NIR raw spectra of both coated and uncoated apple slices were processed by various pre-processing methods, such as standard normal variate transformation (SNV), multiplicative scattering correction (MSC), first derivative (1^{st}D), and second derivative (2nd D). MSC and SNV effectively remove the effects of non-uniform scattering and particle size from the spectrum (Maleki, Mouazen, Ramon, & De Baerdemaeker, 2007). First derivative eliminates the baseline variations, while the second derivative separates overlapping peaks and sharpens spectral features (Wu, Walczak, Massart, Prebble, & Last, 1995). Savitzky–Golay with a gap of 15 points and second-order polynomial filtering was used to smooth each spectrum before derivatives transformation. These spectral pre-processing methods were investigated and optimized based on the coefficient of determination (R^2), and the root mean square errors estimated by prediction (RMSEP).

2.6.4. Development of calibration models

Calibrations and predictions of moisture content in C-A and UC-A slices were developed using PLSR. PLSR is a bilinear factor model which fits a linear regression by projecting the predictors and responses to a new space, called latent variables (LVs), with the best predictive power. In PLSR, leave one out cross-validation was to find the optimal number of **LVs** to be used in calibration. It was determined at the minimum value of the root mean squared error of cross-validation (RMSECV). The absorption spectra were mean-centered before developing calibration models.

2.6.5. Validation and evaluation of developed calibration models

It is important to carry out model validation after model training. Once the calibration models have been developed, it is mandatory to evaluate the generalization and reliability of the developed calibration models in predicting the parameters of unknown samples to ensure that the derived model is representative and will work in the future for new, similar data.

Calibration data were used to develop the calibration model, and the validation data were used to assess the model's performance. The predictive capability of the model was evaluated based on root mean square error of calibration (RSMEC), root mean square error of prediction (RMSEP), coefficient of determination for calibration (R_c^2) and coefficient of determination for prediction (R_p^2). Generally, a good model should have high R^2 with low RMSE values. For better evaluation, the ratio between RMSEP and RMSEC was introduced. This ratio gives information about the tendency of the model to overfit, and the lower value indicates a lesser tendency.

2.6.6. Selection of feature wavelengths

Variable selection is an essential step in multicollinear spectral data. It aims to reduce the spectral data by identifying a few important spectral wavelengths (WL) that capture the highest amount of information from the original spectra. In this study, the variables importance in projection (VIP) scores resulting from the PLSR model were used to select feature WL for moisture monitoring during drying of apple slices (ElMasry, Wang, Vigneault, Qiao, & ElSayed, 2008). Since the mean of squared VIP scores is equal to 1 (Chong & Jun 2005), this value was taken as a cut-off to define important variables.

2.7. Statistical analysis

All the moisture content values were reported as mean ± standard deviation. Statistical analysis was performed in R (Version 3.6.3., R Foundation for Statistical Computing, Vienna, Austria). Parametric one-way ANOVA with Tukey's honest significance difference test was conducted to detect the differences between the means at a 95% confidence interval level. PCA, PLS, and spectral data pre-processing were performed using MATLAB software, Version R2020b (The Mathworks, Natick, USA) and PLS_Toolbox 862 (Eigenvector Research, USA).

3. Results and discussions

3.1. Overview of spectral characteristics of coated and uncoated apple slices during drying

The average spectrum of the coated (C-A) and uncoated (UC-A) slices at different drying times monitored by miniature NIR spectroscopy are shown in Fig. 2a and b, respectively. All the analyzed samples showed a similar spectral trend, featured by main absorption bands at 970–1000 nm, 1200 nm and 1450–1475 nm. The absorption peak at 970–1000 nm is associated with the second overtone of O–H stretching band in sugars (González-Caballero, Sánchez, López, & Pérez-Marín, 2010; Omar, Atan, & Matjafri, 2012). The second overtone of C–H stretching in sugars usually causes the absorption peak between 1100 nm and 1200 nm (Tang, He, Li, & Li, 2018). The last absorption peak was observed at about 1450 nm due to water, related to the first overtone of the O–H stretching band and a combination band (Osborne, Fearn, & Hindle, 1993). According to a study by Beganović et al. (2020), this region of water bands also overlaps with the first overtone of O–H group of carbohydrates (1470 nm). It can also be seen in Fig. 2a and b that the spectra of the coated and uncoated samples showed some different features with respect to the drying time and each other. In particular, the water absorption band at 1450 nm is shifted towards lower absorption as the drying time increases for both cases.

Table 1
Moisture content (MC) [dry basis (d.b.)] during drying for coated and uncoated at 60 °C and air velocity 2 m/s.

Sample	Initial MC (d.b.)	Final MC (d.b.)	Drying Time
Coated	9.67 ± 0.82	0.11 ± 0.05	115 min
Uncoated	5.93 ± 0.12	0.9 ± 0.09	90 min

Other researchers observed a similar trend in absorption spectra. For example, Pu and Sun (2015) studied the moisture distribution of mango slices during microwave-vacuum drying using NIR and reported that those with higher moisture content have a relatively higher absorption.

Similarly, the O–H absorbance band at 975 nm, associated with the presence of sugar, can be seen reducing in intensity as the drying progresses. According to Golic, Walsh, and Lawson (2003), sugar O–H absorption frequencies are sensitive to water, sugar, and temperature. The removal of water induces the concentration of sugar and other dissolved solids. The decrease in water concentration and a subsequent increase in sugar concentration leads to a decrease in the total number of H-bonds (sugar–water and water–water bonds), which in turn is associated with decreased absorption.

The mean absorption spectral curves of the coated and uncoated apple samples at their initial and final moisture content at WL ranging from 900 to 1700 nm are shown in Fig. 2c. As can be seen, both C-A and UC-A slices at their initial moisture content (IMC) had higher absorption intensity and absorbed more energy at any WL compared to samples at their final moisture content (FMC). This is because the presence of water on the surface affects the absorptive properties, thereby resulting in deeper light penetration and subsequently higher absorbance in samples with higher moisture content. However, it can be observed that coated samples, despite having higher FMC, showed a lower absorbance than the uncoated samples.

This decrease in sample absorbance can be related to the homogenous coating formation. The coating formulation consists of several additives, including plasticizers and surfactants. Plasticizers are non-volatile compounds usually of low molecular weight. The low molecular size of a plasticizer allows occupying of intermolecular spaces between polymeric chains. The addition of AMG as a plasticizer might be interrupting H-bonding between water and sugar molecules. Therefore, it can be said that these additives alter the absorbance properties, and because of this reason, coated samples showed a lower absorption on the formation of a uniform coating layer onto the surface of the final product.

Fig. 2d shows the average moisture content (d.b.) for coated and uncoated apple slices against the drying time for temperature of 60 °C and air velocity 2 m/s. It can be seen that the moisture content decreased rapidly for about 30 min and after that it slowed down and then tended to reach an equilibrium state. Table 1 reports the initial and final moisture (dry basis) of the samples and the drying time. Coated apple samples needed a longer drying time (115 min) than uncoated apple slices, which took 90 min to reach a constant weight. This is because the coated apple slices had a higher initial moisture content (9.67% d.b) than uncoated apple slices, which had an initial moisture content of 5.93% d.b.)

3.2. Spectra investigation using PCA

PCA was applied to the spectral data to see patterns within 10–15-min intervals that reflect moisture loss progression and to monitor the drying process qualitatively.

The underlying reason for choosing this statistical approach was to group sample spectra into 10–15-min intervals that reflect the progression of moisture loss and to monitor the drying process qualitatively. Fig. 3 (a and b) shows the PCA scores plot developed from this data array. The first two principal components (PCs) sufficiently described

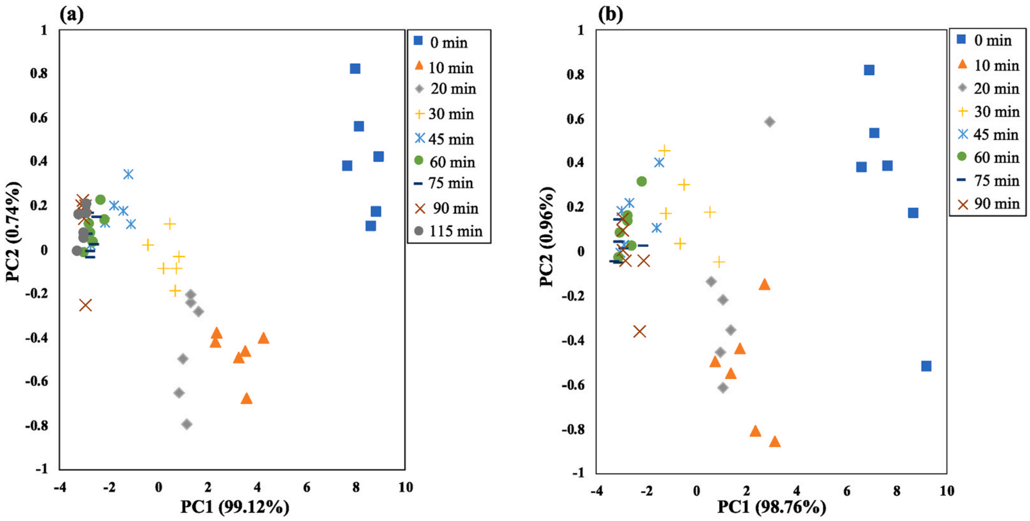

Fig. 3. PCA score plots of the NIR spectra of the coated (a) and uncoated (b) apple slices at various time intervals.

Table 2
PLSR calibration parameters of the NIR spectra for predicting moisture content (%) in apple slices during drying.

Sample	Pre Processing	LVs	Calibration		Cross-Validation		Prediction		RMSE Ratio
			R_c^2	RMSEC (%)	R_{cv}^2	RMSECV (%)	R_p^2	RMSEP (%)	
Apple slices (Coated &uncoated)	Raw	10	0.98	0.29	0.94	0.63	0.95	0.52	1.79
	1st D	9	0.97	0.39	0.91	0.75	0.94	0.81	2.07
	2nd D	4	0.96	0.50	0.89	0.86	0.94	0.70	1.40
	SNV	8	0.96	0.52	0.86	0.94	0.91	0.81	1.55
	MSC	8	0.96	0.52	0.89	0.84	0.91	0.81	1.55

RMSE ratio = RMSEP/RMSEC.

the variation in the spectra for both coated (99.86%) and uncoated (99.72%) samples (Fig. 3a and b). The first PC (PC1) covered the whole spectral data set correlated to moisture content from highest moisture to lower moisture (right to left) in the score plots. A clear separation along the drying time can be observed for both coated (Fig. 3a) and uncoated (Fig. 3b) samples, especially in the first 30 min of drying. The X-loading plot (Fig. S1, supplementary information) displayed 3 maximas at 975, 1200, and 1450 nm, which can be attributed to the difference between R–OH bands of sugar, combination peaks of C–H for sugar, and combination peak of O–H vibrations in water, respectively. The loadings of PC2 show the same features as for PC1. However, it must be noted that the water band at 1450 nm exhibits a stronger influence in PC2 for both coated and uncoated apple slices. Based on the loadings and clustering in the score plots, it can be concluded that the variation in the sugar and moisture content are the main factors represented in the PC1 and PC2.

3.3. Calibration models at full wavelength

In this study, a combined PLSR model was developed to predict the moisture content of tested coated and uncoated apple slices from the spectral data over the full spectral range of 900–1700 nm. The performance of the PLSR model for determining the moisture content of apple slices (both coated and uncoated samples combined) are shown in Table 2. Different spectral pre-treatment techniques were also tested to evaluate the effect of these treatments on model performance for predicting moisture content. As mentioned previously, these pre-treatments have been proposed to eliminate or reduce spectral variations. However, the best data pre-treatment method is highly dependent on the specific application and spectral data (Faber, Duewer, Choquette, Green, & Chesler, 1998). The variable results obtained by spectral pre-treatment in coated and uncoated samples can be explained by the fact that these different pre-treatment methods rely on different assumptions about the structure of the spectral distortion. Furthermore, spectral pre-treatment may also change the systematic part of the data, and this may happen in an advantageous or disadvantageous manner depending on the shape of the spectra. In this study, models derived from raw spectra for apple slices tended to show better performance than those based on pre-treated spectra. For this reason, only models based on raw spectra will be discussed in the following sections. This result is in accordance with other researchers (Kamruzzaman et al., 2016), who also observed that models having the highest R^2 and lowest RMSEP corresponded to data from the raw spectra.

Using the raw spectra of coated and uncoated apple slices, the developed combined PLSR model with 10 LVs (R_c^2= 0.98 and RMSEC = 0.29%) was applied to independent test set, and good prediction results were obtained (R_p^2= 0.95, RMSEP = 0.52%). Since the model have good prediction correlation coefficient (R_p^2) and lower RMSEP values (indicating better fitting results and smaller prediction errors), it can be said that these developed models were adequately promising. Moreover, the R_p^2 obtained in this study was higher than the same obtained for dry matter in apples using a benchtop NIR (Møller, Travers, Bertram, & Bertelsen, 2013), thereby indicating the efficiency and accuracy of miniature NIR over the benchtop counterpart. Additionally, the PLSR model developed from raw spectra showed RMSEP/RMSEC ratio (≤1.8), indicating higher robustness. To visualize the performance of the best PLSR model, the measured moisture content values obtained from the laboratory analysis and its predicted values resulting from the PLSR models are shown in Fig. S2 (supplementary information).

3.4. Selection of feature wavelength

Often, spectral data consists of a large number of variables that can be difficult to manage and process efficiently. Therefore, identifying and

Table 3
Performance of PLSR based on raw spectra using selected key wavelengths over the model developed with full spectral range.

Sample	Model	LVs	Calibration		Cross-Validation		Prediction		RMSE Ratio
			R_c^2	RMSEC (%)	R_{cv}^2	RMSECV (%)	R_p^2	RMSEP (%)	
Apple Slices (Coated and Uncoated)	PLSR	10	0.98	0.29	0.94	0.63	0.95	0.52	1.79
	SWL-PLSR	7	0.93	0.64	0.91	0.89	0.92	0.71	1.10

RMSE ratio = RMSEP/RMSEC.

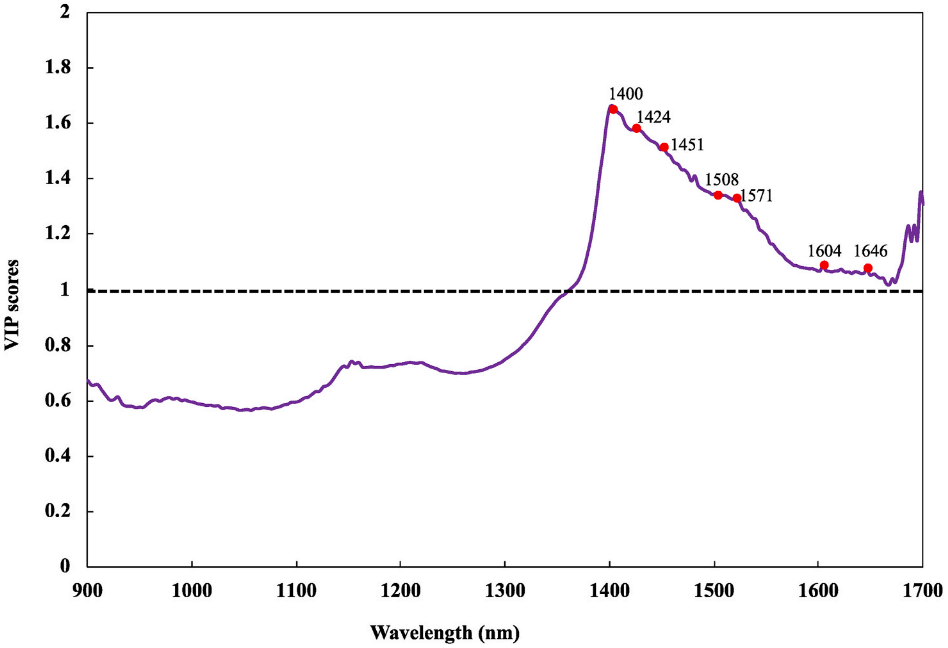

Fig. 4. Selection of optimal wavelength using VIP scores.

selecting a few key variables from the spectral data is critical in spectral analysis. In the present study, the variables importance in projection (VIP) scores resulting from the PLSR model were used to select feature WL for moisture monitoring during drying of apple slices. Fig. 3 shows the wavelength importance for bands indicated by the VIP method. The black dashed line represents the threshold (one) and the important WL are those with scores greater than one. Using this approach, 7 important WL (1400, 1424, 1451, 1508, 1511, 1604 and 1646 nm) were selected from the full spectral range. Although there were other WL that showed a higher value of VIP scores, those did not increase the predictive power of the model and therefore, those were not considered. The absorption at 1400, 1424, 1451, 1508, and 1511 nm was associated mainly with the overtones and combinations of the O–H bond stretching vibration in the water. Given that water is a major constituent in apples, it was evident that the most important WL in the NIR region were associated with water absorption bands.

3.5. Calibration models at feature wavelengths

Further, these methods can reduce the number of variables and show the important variables that have an effect on the viability of soybean seeds. From a practical point of view, the selection of variables can make the future acquisition of data cheaper and less time-consuming.

Once the important spectral WL were identified, the PLSR models were developed with these 7 WL (denoted as PLSR-SWL), and the results are presented in Table 3. The SWL-PLSR model had a good performance in predicting moisture in coated slices with $R_p^2 = 0.93$, and RMSEP = 0.63%. The SWL-PLSR model performance in coated samples was comparable to the PLSR model developed with full spectra, though 96.92% (7 out of 228) of the variable were eliminated. Overall, only seven SWL in the spectral region between 1400 and 1650 nm (Fig. 4), which contains the absorption band of water, effectively predicted the moisture content of both coated and uncoated apple slices at different drying times. These seven SWL is almost equal to full WL as these carry the most spectral information. It enables a single simple sensor instead of hundreds of variables and more complex and slower sensors. As a result, both accuracy and speed can be assured that is important for real-time industrial implementation. Overall, the technique of WL selection provides a detailed analytical view of moisture content in C-A and UC-A slices during drying, which could be used to explore the design of a filter-based spectral instrument for non-destructive and rapid estimation of moisture content. These results can be useful to develop simple and cost-effective miniature NIR sensors for more practical and faster applications in the food industry.

4. Conclusions

The present study outlines the evaluation and application of chemometric models together with miniature NIR spectroscopy to monitor, in real-time, the moisture content during drying of apple slices, with and without coatings in a hot air-dryer. PCA and PLSR were evaluated for their potential in qualitative and quantitative monitoring of residual moisture content in coated and uncoated samples. The PCA analysis of the spectral data was able to differentiate samples based on a decrease in moisture content along the drying time. This is useful to track the variances evolving mainly from water evaporation, as the spectral differences reflect the resonance bands of the O–H stretching of water. The PLSR provided satisfactory results for the optimal prediction of moisture content. The VIP scores provided an accurate and efficient methodology for selecting important variables. This is the first reported study to utilize miniature NIR spectroscopy along with chemometrics for accurate, rapid, and non-destructive evaluation of drying behavior of apple slices with or without coatings. Furthermore, this study addressed developing a fast, reliable, and accurate system for real-time monitoring of the moisture content of apples by selecting three important wavelengths. Future research on testing the robustness of various other strategies to identify feature wavelengths should also be investigated using different commercially available low-cost spectral sensors for predicting moisture content in apples during the drying operation.

CRediT authorship contribution statement

Ragya Kapoor: Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Amir Malvandi:** Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Hao Feng:** Resources, Writing – review & editing, Supervision, Funding acquisition. **Mohammed Kamruzzaman:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lwt.2021.112602.

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