Chapter

Application of Visible to Near-Infrared Spectroscopy for Non-Destructive Assessment of Quality Parameters of Fruit

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Abstract

The accuracy and robustness of prediction models are very important to the successful commercial application of visible to near-infrared spectroscopy (Vis-NIRS) on fruit. The difference in physiological characteristics of fruit is very wide, which necessitates variance in the type of spectrometers applied to collect spectral data, pre-processing of the collected data and chemometric techniques used to develop robust models. Relevant practices of data collection, processing and the development of models are a challenge because of the required knowledge of fruit physiology in addition to the Vis-NIRS expertise of a researcher. This chapter deals with the application of Vis-NIRS on fruit by discussing commonly used spectrometers, data chemometric treatment and common models developed for assessing quality of specific types of fruit. The chapter intends to create an overview of commonly used techniques for guiding general users of these techniques. Current status, gaps and future perspectives of the application of Vis-NIRS on fruit are also discussed for challenging researchers who are experts in this research field.

Keywords: near-infrared spectroscopy (NIRS), chemometrics, multivariate data, fruit quality

1. Introduction

The quality of fruits is produced in the orchard or garden and only maintained during postharvest storage [1]. This necessitates accurate determination of the optimal harvest time and a deeper understanding of physiological changes occurring in fresh fruit during storage. The main goal of postharvest management is to delay senescence by reducing the ripening processes and other physiological processes such as respiration [2]. The quality of fruit at commercial consignments is commonly assessed using techniques such as reflectometer-based determination of total soluble solutes (TSS), fruit mass or firmness tests [3]. The fruits selected as samples for assessment of parameters such as juice TSS are wasted because after they are destructed they cannot be returned to the batch. Therefore, the quantity sent by a farmer does not reach the destined market in its original quantity. Moreover, the fruits taken as samples may not properly represent the actual status of the batch. The challenge of sample size is significant in huge farms that require a large number of representative samples. It is also known that fruits from the same batch, same tree and the same branch of a tree are likely to differ in quantities of their quality parameters. It is therefore necessary to find non-destructive alternative techniques that can be used to analyse the entire batch without losing any samples.

Techniques such as mass and firmness determinations do not destruct sample fruit. However, most fruits are very perishable and develop bruises if they experience successive external impact [4, 5]. Moreover, the physical parameters such as mass and firmness cannot be associated to organoleptic qualities with accuracy. A big fruit does not warrant a better taste than a small fruit. Therefore, the elevated purchase price of big fruit based on mass is not a justified technique for customers. The firmness tests can be used to determine the level of ripeness and associated with the edibility of climacteric fruit such as avocado and mango. However, the firmness cannot be directly associated to flavour because flavour is determined by the levels of certain biochemical compounds that should be analysed from the consumed fruit part. It is for these reasons that application of spectrometers is necessary since they can analyse quantities of biochemical compounds without excessive contact with a fruit. Spectrometers can be a very useful tool for growers who want to non-destructively determine fruit parameters that are used to track optimal time of harvesting. Application of hand-held spectrometers on hanging fruit can eliminate the estimation of harvest time using few samples that sometimes do not fully represent the entire orchard [6, 7]. Moreover, they preserve the sample fruit that would be wasted if destructive methods were used. In postharvest storage, visible and near-infrared spectroscopy (Vis-NIRS) can be applied in various forms where fruit would be passed under a radiation chamber and be analysed for physical, chemical and organoleptic properties whilst rolling on sorting belts [8]. The Vis-NIRS holds many advantages over destructive or contact techniques. Analyses of every fruit in a batch, mechanised precision that lasts longer than human effort and reduction of fruit waste as a result of specified management are among major benefits that can be obtained from Vis-NIRS applications.

2. Spectrometers commonly applied in acquisition of spectra from fruit

The trade names may differ from one supplier to the other. However, the type of spectrometers commonly used can be properly categorised based on their operation mode. Vis-NIRS operates in three common modes: the reflectance, transmittance and interactance (diffuse reflectance) modes [9]. Reflectance is the most common mode of acquiring spectra from fresh fruit. Although it can be associated with the type of spectrometers commonly available, it is also a less restricted mode compared to others. Other modes such as transmittance would require that the radiation passes through the sample fruit which is sometimes inefficient because radiation may not reach the other side of a fruit due to disturbances such as a stone, seeds or hollow spaces inside the fruit. Hereon, the common spectrometers applied on specific fruit types will be reviewed and associated with the botanic characteristics of the fruit.

2.1 Stone (drupe) fruits

Stone fruit, also called drupe fruit, is an indehiscent fruit characterised by a thin sheet as exocarp, fleshy mesocarps and a hard endocarp. The hard endocarp usually contains a single seed and is referred to as a stone because of its high firmness [10]. Examples of drupe fruit are peaches, nectarines, plums, lychees, mangoes, avocados and cherries. Application of Vis-NIRS on stone fruit for assessing organoleptic parameters requires awareness about the stone that can interfere with radiation. As a result, most researchers would avoid using spectrometers that use transmittance mode as most radiation is likely to be deflected or absorbed by the stone inside the fruit. Spectrometers working on reflectance and interactance modes are the most relevant methods if the analysis is not associated with a stone [11]. The choice of a spectrometer can depend on the assessed fruit quality. Transmittance mode would be appropriate if the objective is to analyse the size or hardness of the stone.

The appropriateness of reflectance mode is achieved when the spectra are collected for assessing parameters in the mesocarp. Assuming that the number of streams illuminated by the spectrometer (n) is 4, **Figure 1** illustrates the assumption of radiation paths the radiation can pass through if the hypothetical radiation is applied in three different modes. One, three or one of the four arrays reaches the sensor if a transmittance, reflectance or interactance mode is used, respectively.

2.2 Berry or aggregate fruits

Botanically, a berry or aggregate fruit is made up of more than one seed containing fruitlets produced from a single ovary [12]. Common examples include citrus, banana, pineapples, cucumber, tomatoes and grapes. The term berry fruit is commonly used to refer to small pulpy fruit with thin coat-like exocarp tissues covering the fleshy edible mesocarp. Examples of fleshy berries are strawberries, raspberries, mulberries, blackberries, blueberries, redcurrants and blackcurrants. The main factor of consideration in application of Vis-NIRS on aggregate fruit is that the fruit is formed as a combination of smaller fruit which can vary in biochemical composition [13]. The uneven ripeness of berry fruit is significant on vine fruit such as grapes, which may necessitate the use of spectrometers that consider each fruit in the bunch as a single fruit. Any mode of spectrometer can be used on aggregate fruit. This is due to their fleshy internal structure and few or tiny seeds interfering with the radiation passing through the fruit. However, the important consideration is that the size of the radiation source is fully covered and the fruit size can enable passage of radiation from the source to the detector if the transmittance mode is used. Lammertyn et al. [14] investigated the distance that a light beam can penetrate into the fruit. The authors found that there was a wavelength-dependent effect that showed that the regions in 700–900 and 900–1900 nm reach around 4 and 2–3 mm,

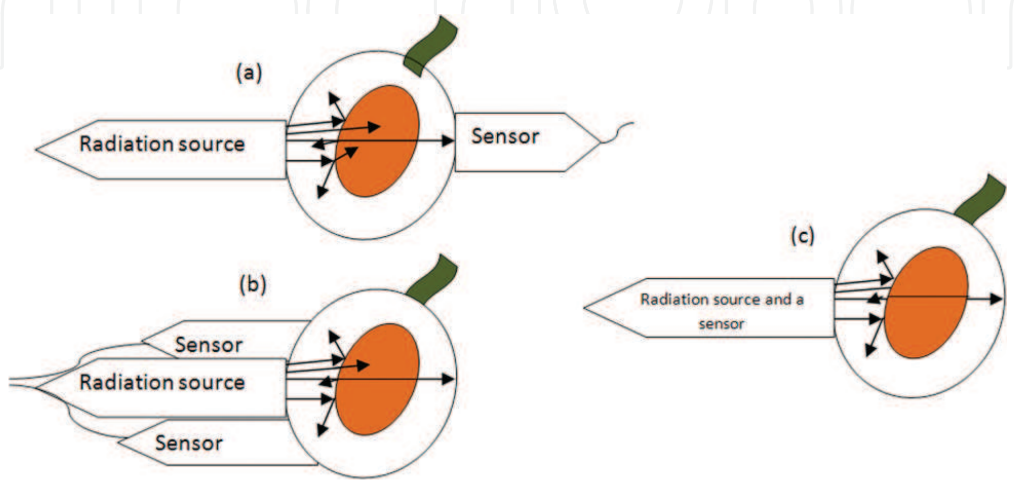

Figure 1.
The assumption of possible radiation pathways inside a stone fruit. (a) Is the transmittance mode, (b) is the illustration of reflectance mode and (c) is the interactance mode and their ability to obtain the required information from only the mesocarp of the fruit.

respectively, which showed that a more intensified illumination was required to obtain a penetration of greater depth if the transmittance spectrum was required.

2.3 Pome fruit

Pome fruit are characterised by a thin exocarp, edible mesocarp and a soft endocarp. Their seeds are in the part called an endocarp or a pit which is relatively harder than the edible mesocarp but softer than the endocarp of stone fruit [15, 16]. Common examples of pome fruit are apples, pears, cotoneaster, crataegus (hawthorn and mayhaw), loquat, medlar, pyracantha, toyon, quince, rowan and whitebeam fruit. Application of Vis-NIRS on pome fruit can be in any form depending on the objective of the assessment. The hardness of endocarp can be used as a measure of maturity of pome fruit [17, 18]. If maturity is assessed, the endocarp is not considered as interference in the transmittance mode which requires radiation to pass through the fruit. However, the endocarp is likely to differ from one fruit to another irrespective of common characteristics such as maturity stage or size. Two fruits of the same maturity stage and the same size may have a different number of seeds. Using transmittance mode can reduce the assessment accuracy when the quality parameters of interest are in the mesocarp.

3. Chemometric treatment of spectral data obtained from fruit

Most spectrometers acquire a full visible to near infrared radiation spectra ranging from 450 to 2500 nm. However, theory suggests that organic components with concentrations higher than 0.1% in fruit have their particular range on the visible or near-infrared wavelengths that result to their best reflection [9]. As such, most researchers always select specific ranges where the analysed compound is likely to respond. However, some fruit quality parameters may be best reflected by the entire spectra [19]. The use of the full spectral range is somehow superior to using specific ranges since it provides a wide source of reference points along the spectrum. The general steps of chemometric analysis applied to spectral data collected from fruit are (i) selecting the wavelength range, (ii) pre-processing raw data to derivatives, (iii) calibrating prediction models and (iv) validating the performance of the developed models on independent external test set. Based on the objective of the study, a researcher can either develop quantitative or qualitative models.

The necessary results that authors show are after validation. The most important model parameters of reference are correlation coefficient (R^2) and the root mean squared error of prediction (RMSEP). A good model is selected based on high R^2 value and low RMSEP value which are the main parameters of consideration, although there are other parameters such as the ratio of performance deviation (RPD) and bias. RPD is widely used as a reference parameter of the performance of prediction models. However, there is lack of information on how was the system developed, and the relationship between the R^2 values and RPD values is in exponential form, whilst it should be linear if both values can be used as references to judge models' accuracy [20]. Therefore, the most necessary parameter is the R^2 value because of its simplicity and a traceable statistical development of its relevance. The R^2 values range from 0 (poor model) to 1 (best model), and anything in between can be related to its proximity to the mentioned extremes. The RPD values cannot be simplified to that level of stating the maximum and minimum values. Several authors refer to Chang et al. [21] who invented the three quality categories of model reliability: excellent models (RPD > 2), fair models (1.4 < RPD < 2) and non-reliable models (RPD < 1.4). However, those authors did not give any statistical basis of the mentioned thresholds.

3.1 Quantitative models

Quantitative Vis-NIRS models are those that estimate the exact quantity of a physical or biochemical compound. They hold a higher advantage in the assessment of quality parameters that cannot be categorised into distinct groups but characterised by a continuous range. Partial least square (PLS) regression (PLSR) is arguably the most used quantitative model by researchers. In PLS models, an orthogonal basis of latent variables is constructed one by one in such a way that they are oriented along directions of maximal covariance between the spectral matrix and the response value [22]. The technique was introduced by Herman Wold in 1975 as an improved modification to overcome collinearity of multiple linear regressions [23]. A unique feature of basic PLS regression is its simplicity. The basic PLS method consists of a series of simple least square optimisation called nonlinear iterative partial least squares NIPALS; [24]. The PLS technique also accounts for noisy and redundant spectral variables and can analyse more than one chemical variables at once.

The majority of recent research reports are based on its different manipulations. As a result, models such as interval partial least squares (iPLS), interval successive projection algorithm (iSPA-PLS), moving window partial least squares (MWPLS) and other PLS modifications were introduced or reinvented in the last decade [25–27]. The PLS modelling was developed by Wold in 1981 [28], and majority of researchers have referred to it as a pivot point of regression models. The following section looks at the common quantitative models for specific types of fruit. Hereon, examples of studies that developed quantitative models for stone fruit and nuts (**Table 1**), berries and aggregate fruit (**Table 2**) and pome fruit (**Table 3**) are reviewed.

Fruit	Assessed quality parameter(s)	NIR mode used	Spectral range	Vis-NIRS models developed	Reference
Almond	Amygdalin content	Diffuse reflectance mode	888–1795 nm	PLS	[29]
Date	TSS, moisture content and colour	Reflectance	285–1200 nm	PCR	[30]
Jaboticaba	Total anthocyanin content	Reflectance	714–2500 nm	iSPA-PLS, PLS and GA-PLS	[25]
Mango	TSS, firmness, TA and rind pitting index	Reflectance	700–1100 nm	PLS	[31]
Olives	Fat content, moisture and free acidity	Reflectance	380–1690 nm	PLS and LS-SVM	[32]
Peach	Days before decay	Reflectance	900–2500 nm	PLS, LS-SVM and MFRG	[33]
Plums	SSC, TA, juice pH, TSS/TA and firmness	Interactance	500–1010 nm	PLS	[34]

LS-SVM, least squares support vector machine; MFRG, multiple fitting regression based on Gaussian fitting function; PLS, partial least squares regression; PCA-LDA, principal component analysis-linear discriminant analysis; SPA-LDA, successive projection algorithm-linear discriminant analysis; GA-LDA, genetic algorithm-linear discriminant analysis; PCR, principal component regression.

Table 1.
Application of Vis-NIRS for assessing quality parameters of stone fruits or nuts.

Fruit	Assessed quality parameters	NIR mode used	Spectral range	Vis-NIRS models developed	Reference
Blackberries, wild blueberries, raspberries, redcurrants and strawberries	Total phenolic compounds and antioxidant activity	Reflectance	904–1699 nm	PLS	[35]
Citrullus colocynthis	Total polyphenol content	Absorbance	700–2500 nm	PLS	[36]
Mandarins and oranges	Mass, colour, fruit diameter, firmness, pericarp thickness and juice mass	Reflectance	1600–2400 nm	MWPLS	[26]
Mulberry	SSC	Reflectance	400–2500 nm	PLS	[19]
Pineapple	Nitrate level	Interactance	600–1200 nm	PLS	[37]
Strawberry	TSS and pH	Reflectance	10,494–3673 cm^{-1}	SIMPLS	[38]
Strawberry	TSS	Interactance	4000–10,000 cm^{-1}	iPLS and MWPLS	[27]
Tomato	Firmness	Reflectance	500–1700 nm	PLS	[34]
Watermelon	Lycopene, β-carotene and TSS	Reflectance	900–1700 nm	PLS	[8]

PLS, partial least squares regression; SIMPLS, soft independent modelling partial least squares regression; iPLS, interval partial least squares; MWPLS, moving window partial least squares.

Table 2.
Application of Vis-NIRS for assessing quality of berry or aggregate fruit.

Fruit	Assessed quality parameters	NIR mode used	Spectral range	Vis-NIRS models developed	Reference
Apple	SSC	Interactance	500–1100 nm	PLS	[39]
Loquat	Moisture content	Reflectance	750–2500 nm	PLS	[40]
Pears	TSS	Reflectance	710–930 nm	PLS	[41]
Pears	SSC	Reflectance	930–2548 nm	PLS	[42]
Pears	SSC and firmness	Absorbance	500–1010 nm	PLS and MLR	[43]
Persimmon	Astringency and tannin contents	Interactance and transmittance	600–1100 nm	PLS	[44]
Wax jambu	Total phenolic compound content	Interactance	1000–2400 nm	PLS	[45]

PLS, partial least square regression; MLR, multiple linear regression.

Table 3.
Application of Vis-NIRS for assessing quality of pome fruit.

Fruit	Classification parameter	NIR mode used	Spectral range	Vis-NIRS models developed	Reference
Almond	Amygdalin content	Interactance	888–1795 nm	LDA, QDA and PLS-DA	[28]
Hazelnuts	Regions and cultivars	Transmittance	650–4000 cm^{-1}	PCA, LDA and PLS-DA	[47]
Almond nuts	Concealed damage	Reflectance	1125–2153 nm	PLS-DA	[48]
Jaboticaba	Cultivars	Reflectance	1000–2500 nm	PCA-LDA, SPA-LDA and GA-LDA	[49]
Macadamia nuts	Variety	Reflectance	11,544–3952 cm^{-1}	PCA-LDA and GA-LDA	[50]
Peach	Cultivars	Reflectance	800–2600 nm	PCA, UVE-PLS and SPA	[39]
Pine nuts	Geographic origin	Reflectance	400–2500 nm	PLS-DA	[51]

LDA, linear discriminant analysis; QDA, quadratic discriminant analysis; PCA, principal component analysis; PLS-DA, partial least squares regression discriminant analysis; UVE-PLS, uninformative variable elimination based on partial least squares; PCA, principal component analysis; SPA, successive projection algorithm; PCA-LDA, principal component analysis-linear discriminant analysis; GA-LDA, genetic algorithm-linear discriminant analysis.

Table 4.
Application of Vis-NIRS for classification of stone fruit and nuts.

Fruit	Classification parameter	NIR mode used	Spectral range	Vis-NIRS models developed	Reference
Blackberries, wild blueberries, raspberries, redcurrants and strawberries	Total phenolic compounds and antioxidant activity	Reflectance	904–1699 nm	PCA	[35]
Citrus	Firmness	Reflectance	400–1750 cm^{-1}	Raman signal	[52]
Mulberry leaf	Pesticide residue	Reflectance	390–1050 nm	PLS-DA	[53]
Nectarine	Variety	Reflectance	360–1795 nm	LDA and PLS-DA	[28]
Strawberry	Organic and conventionally grown fruit	Reflectance	12,500–3600 cm^{-1}	PLS-DA	[38]
Tomato fruit	Ripeness	Interactance	400–1000 nm	PLS-DA	[54]
Tomato fruit	Lycopene content	Reflectance	275–1150 nm	PLS-DA	[55]

LDA, linear discriminant analysis; PCA, principal component analysis; PLS-DA, partial least squares regression discriminant analysis.

Table 5.
Applications of Vis-NIRS for classification of berry or aggregate fruit.

Fruit	Classification parameter	NIR mode used	Spectral range	Vis-NIRS models developed	Reference
Apples	Cultivars	Reflectance	4000–10,000 cm^{-1}	Fuzzy linear discriminant analysis and fuzzy c-means clustering	[56]
Apples	Bitter pit	Reflectance	971.2–1142.8 nm	QDA and SVM	[57]
Apples	Bitter pit	Reflectance	935–2500 nm	Spectral pattern recognition	[58]
Apples	Cultivars	Reflectance	1000–2500 nm	PCA	[59]
Apples	Separating organic and inorganic fruit	Reflectance	900–1700 nm	Spectral pattern recognition and PLS-DA	[60]
Apples	Internal browning	Reflectance	740–1040 nm	Spectral pattern recognition	[61]
Chinese quince fruit	Varieties	Reflectance	1000–2500 nm	LDA, QDA and SVM	[62]
Persimmon fruit	Fruit origin	Reflectance	740–2700 nm	PCA and LS-SVM	[63]

LDA, linear discriminant analysis; QDA, quadratic discriminant analysis; PCA, principal component analysis; PLS-DA, partial least squares regression discriminant analysis; SVM, support vector machine; PCA, principal component analysis.

Table 6.
Application of Vis-NIRS for classification of pome fruit.

3.2 Classification models

Most fruit growers classify their crop into different quality classes in order to state their selling price and target different markets. Fruit destined for a local market may not be at the same level of quality as fruit destined for exports to international markets. Fruit can be sorted based on their maturity level, colour, origin, size and other characteristics of interest to consumers. This necessitates an effective way of classifying many fruits at short period of time. The Vis-NIRS technique has been shown to have an ability to assess a minimum of three fruits per second [46], which is way faster than the potential of a human panel normally used on commercial scales. The following tables exemplify the studies that demonstrated the ability of Vis-NIRS to classify stone fruit and nuts (**Table 4**), berry and aggregate fruit (**Table 5**) and pome fruit (**Table 6**). Notably, researchers have an extended freedom of choice in selecting classification models compared with quantification models. However, partial least square discriminant analysis (PLS-DA) and linear discriminant analysis (LDA) are the commonly used models for fruit. Discriminant analyses use a principal component analysis (PCA) for extracting, compressing and screening multivariate data such as spectra. The PCA technique employs a mathematical procedure that transforms a set of response variables into a set of non-correlated variables called principal components. PCA produces linear combinations of variables that are useful descriptors or even predictors of some particular structure in the data matrix [64]. Although typically used for spectral data, different classification models can also be used for mapping data matrix of any type.

4. Current status of spectroscopy application on fruits

4.1 Vis-NIRS application on fresh fruit

There are a great number of studies demonstrating the capability of Vis-NIRS to accurately assess biochemical and physical quality parameters of fruit. The commonly assessed compounds of fresh fruit include sugar contents, acidity, juice pH, pectin, firmness, etc. because of their direct link with being referred to as sorting categories [9]. Secondary factors of quality such as bruising, scars and other disorders are not commonly assessed. However, some studies have assessed factors indirectly associated with fruit quality such as postharvest disorders. The ability of Vis-NIRS to assess invisible internal disorders such as brown heart disorder of pears has been demonstrated [65]. Magwaza et al. [66] demonstrated the ability of Vis-NIRS to detect rind breakdown disorder of mandarins. The detection of presymptomatic attributes leading to disorders has also been demonstrated successfully on fresh fruit. Ncama et al. [67] demonstrated the ability of Vis-NIRS to detect susceptibility of fresh grapefruit to rind pitting disorder occurring in postharvest storage. The extent of Vis-NIRS application has been reported from the stable laboratory-based instruments, portal instruments and in sorting lines. The most fascinating studies were those that demonstrated the ability of Vis-NIRS to assess the quality of fruit in motion on sorting lines. Salguero-Chaparro and Peña-Rodríguez [32] successfully quantified the contents of fats, free acidity and moisture of intact olives using a system mounted on the conveyer belt. Such studies were a clear demonstration of the period at which commercial fruit growers should adopt the Vis-NIRS technique for sorting their fruit.

4.2 The application of Vis-NIRS on secondary products from fruits

Studies demonstrating the ability of Vis-NIRS on assessing quality of slices of fresh fruit are common. The importance of monitoring their quality can be associated to their altered respiration rate which may result to degradation of their quality at an elevated rate. Fruits have hard sheet-like peels that regulate their respiration and protect the flesh from carbon dioxide that leads to development of the browning pigments. It is for this reason that careful quality management is crucial after removing the exocarp of fruit.

Dried fruits have little biological activities occurring during their storage. As such, they have extended life span compared to fresh fruit. Their low biological activities only necessitate the determination of parameters associated to edibility such as taste and flavour only once immediately after the drying process. When fruits are dried, their taste parameters are nearly fixed. After the drying stage, the necessary factors to analyse are the protective substances such as biochemical compounds related with antifungal or antibacterial activities if their quality is also threatened by infections. On the other hand, juices and wines are judged by holding true to the manufacturer's flavour. This therefore calls for each and every bottle to hold similar characteristics to keep a trusting trade with customers. It is not the flavour-related parameters that require rapid assessment using Vis-NIRS but secondary metabolites associated to flavour such as phenolic compounds, vitamins, chloride, sulphate and mineral contents [68, 69]. The maturity stage (alcohol strength) of wines during fermentation can increase the accuracy of management. Rapid determination of titratable acidity of apple wine using Vis-NIRS during the fermentation process was demonstrated by Peng et al. [70].

Wine ageing in wooden barrels is aligned with improved final sensory profile and, therefore, price of purchase. It is for this reason that the process used during wine ageing needs to be traceable for insurance of trustworthy trading standards. Basalekou et al. [71] demonstrated the ability of Vis-NIRS to discriminate different wines based on variety, type of barrel and ageing time. Magdas et al. [72] demonstrated rapid discrimination of wines based on variety, vintage and geographic origin. The shelf life of wines and juices may also be predicted inversely by determination of fermentation and adulteration compounds. The common spectra acquisition mode used on liquid fruit product is the transmittance mode. This is due to the uniformity of the liquid texture which does not deflect radiation throughout the sample. The light that is not absorbed by the liquid is then reported to a spectrometer as an absorbance spectrum. Fourier transform Raman spectroscopy method is the common type of spectra collected [73, 74]. However, Teixeira dos Santos et al. [69] revealed a better suitability of mid-infrared spectroscopy (87.7% of correct predictions) over near-infrared (60.4%) and Raman spectroscopy (60.8%) on classifying wines based on geographic origin.

5. Future perspectives

There are a lot of studies that demonstrated the ability of assessing quality of fruit by application of Vis-NIRS. The application of Vis-NIRS has been tested and approved on many varieties of fruit from different geographic conditions. Different data collection, pre-processing and chemometric analysis methods and different kinds of prediction models have been developed and demonstrated to accurately assess fruit quality. The next research step in this field is very hard to point out. Arguably, it is the right time to consider Vis-NIRS as an ordinary method of assessing quality parameters of fruit. Studies with an objective of demonstrating the application of Vis-NIRS with different modes, on different fruit or fruit cultivars, or using different chemometric methods and selecting the best method are no longer contributing any novelty of interest in research. Such experiments are most relevant to technicians who want to calibrate spectrometers for use in commercial lines but not as research investigations.

Significant recent research reports on demonstrating new application methods and new chemometric techniques or developing new types of models. To our knowledge, no report has defied the accuracy of PLS models. The reports then become unnecessary from the application point of view. As long as the ordinary PLS model or its modified forms are able to obtain 97% prediction accuracy on analysing TSS [75, 76], they are better than using the destructive reflectometer technique. As long as PLS models can obtain 90% accuracy on analysing total phenolic compounds [77, 78], they are better than the use of procedures based on protocols involving the use of chemicals and sophisticated laboratory equipment. Illustrating ways of increasing the accuracy of PLS models is of course important, but it does not contribute any novelty in the research. Vis-NIRS has been demonstrated in online systems [32], which should have been a signal that it is no longer new and can be a commonly used technique. The only novelty of intrigue to technicians would be developing models that hold 100% accuracy, which is also not astonishing because Vis-NIRS models are assessed based on predicting reference values of a parameter that is assessed by destructive techniques. Destructive techniques may have had errors and inaccuracies that arose from a non-calibrated human potency. Vis-NIRS can accurately predict incorrect reference data and create a precise model with incorrect calibration.

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6. Conclusion

The research world has greatly demonstrated the potential of Vis-NIRS application for assessing quality of fruit. But the technique is still not common on commercial lines. The Vis-NIRS scarcity on commercial lines could be associated to the expensive prices of the spectrometers compared to weighing scales. As such, most supermarkets may choose to use the mass of fruit to determine the purchase price although not accurate since a big fruit does not give a warrant of a satisfying flavour. The fresh horticultural produce industry is one of the few food industries that do not indicate the nutritional characteristics of their product. Most processed food stuff has a table of contents of carbohydrates, fats, vitamins, etc. indicated on their containers. Customers nowadays are willing to pay extra prices for high nutritious fruit [9]. The nutritional information of fruit could be easily indicated if the Vis-NIRS technique is adapted in the market. Therefore, trustworthy trade relationship could be easily achieved since the biochemical components of fruit could be associated with the purchasing price. Buying the instrument is a once-off expense that will improve the industry for as long as there is no other superior technology invented. The next step in research should focus on gathering information or reasons that result to distributors and end market sellers not willing to adapt using Vis-NIRS. Teaching the public about Vis-NIRS is necessary because most people are not scientists and may not understand the safety of applying radiation on their food. It should be remembered that some people believe that biotechnology used to produce genetically modified organisms is a source of toxic food escalating diseases such as cancer [79].

Conflict of interest

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