Near-Infrared Hyperspectral Imaging Techniques for Non-Destructive Quality Assessment

Subjects: Spectroscopy

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Hyperspectral imaging (HSI) is one of the most often used techniques for rapid quality evaluation for various applications. It is a non-destructive technique that effectively evaluates the quality attributes of root and tuber crops, including yam and cassava, and their food products. Hyperspectral imaging technology, which combines spectroscopy and imaging principles, has an advantage over conventional spectroscopy due to its ability to simultaneously evaluate the physical characteristics and chemical components of various food products and specify their spatial distributions. HSI has demonstrated significant potential for obtaining quick information regarding the chemical composition of the root and tuber, such as starch, protein, dry matter, amylose, and soluble sugars, as well as physical characteristics such as textural properties and water binding capacity.

hyperspectral imaging spectroscopy quality evaluation yam cassava image processing

1. Introduction

The world's tropics and subtropics depend on root and tuber crops such as cassava, yam, potato, and sweet potato as critical staple foods that are consumed in various ways [1]. Additionally, they serve as the starting point for small-scale industrial production, particularly in underdeveloped nations [2]. Nearly 700 million people in subtropical and tropical areas mainly obtain carbohydrates and energy from cassava (Manihot esculenta Crantz) root [3]. The leaves also supply protein, vitamins, and minerals [4]. The roots have a dry matter composition of 80 to 90% carbohydrates, of which 80% is starch and the other minute amounts are sucrose, glucose, fructose, and maltose. They also contain about 0.1– 0.5% fat, 1–3% protein, and 80–90% carbohydrates, respectively. Yam (*Dioscorea* spp.) is another staple crop cultivated in Africa, Asia, South America, the Caribbean, and the South Pacific [5]. Generally, it provides energy ranging between 80 and 120 kcal/100 g, depending on the variety. The moisture content of fresh tubers ranges between 58 and 80%, 0.5–1.2% for ash, 17.5–28% for carbohydrates, 1.5–6% for crude protein, 0.1–0.2% for fat, and 0.6–1.5% for fiber, on a wet basis [3]. Cassava and yam breeding programs need to evaluate many genotypes for agronomic parameters, nutritional composition, and end users' preferred attributes to facilitate the breeding of crops with top-performance quality and increase adoption by farmers and processors. However, evaluating these traits is cumbersome, as it is costly and time-consuming, especially when using conventional approaches. Therefore, this brings to the fore the necessity to provide a cost-effective, timesaving, and accurate prediction of those important traits to make informed decisions in the selection process, especially in large breeding populations.

Near-infrared spectroscopy (NIRS) has proven to be a reliable tool for predicting various quality parameters in many breeding programs, such as cassava, yam, potato, and sweet potato [1][6][7][8][9][10][11]. Its application in breeding programs has improved, as it enhances the adoption of modern NIRS and has been used to accurately predict key quality traits, as reported by many authors on genetic technologies that require the phenotyping of many clones for complex features within the shortest time possible and at minimal cost, especially at the early breeding stages [8]. NIRS has been used to evaluate many quality traits in crops, and their flour, with a good to a medium coefficient of prediction, as reported in [1][12][13][14][15][16][17].

To highlight the potential of NIRS for the investigation of numerous chemical constituents, Alamu et al. [18] wrote a review which shows that NIRS has potential as a high-throughput phenotyping tool for root and tuber crops. Additionally, their research showed that most published studies supported the ability of NIRS to accurately predict biochemical parameters such as starch, soluble sugar, and many others. However, there are only a few studies confirming the possibility of NIRS predicting other quality attributes related to end-product quality, which inform consumers' preferences. These are seemingly complex traits because the quality of the product has been impacted by processing factors [18]. However, the emergence of near-infrared hyperspectral imaging (NIR-HSI) represents a new development in the application of spectroscopy. By combining the spatial and spectral data of the target sample, this method merges imaging and spectroscopic concepts with the ability to capture additional inherent information about the product. It can accurately predict the biochemical properties, physical (internal and external) features, and spatial information of the chemical components in the products [19]. It has gained broad interest in the noninvasive quality monitoring of many food crops [19].

NIR-HSI was originally developed for remote sensing applications, but it is now used to facilitate complete and reliable analyses of the inherent physical and chemical properties of food products [20]. Recently, many authors have reported using NIR-HSI to assess quality attributes in food and other products [21][22][23][24]. In addition, it has been extensively used for the physical and biochemical constituent characterization of potatoes and sweet potatoes [25][26][27][28][29][30].

2. Overview of Near-Infrared Reflectance Spectroscopy (NIRS)

NIRS is a fast, non-destructive analytical technique widely used to analyze organic constituents and other properties in various agricultural products with minimum or no sample preparation steps [31]. It employs a wavelength between 780 nm (12,500 cm^{-1}) and 2500 nm (14,000 cm^{-1}), providing more complex structural information about bond vibration behavior. Chemical bonds between light atoms in molecules such as C, N, O, and H with primary absorption in the infrared (IR) region have strong vibrational overtones and combination bands that absorb light in the near-infrared (NIR) region (780–2500 nm) of electro-magnetic radiation. The NIRS region in the electromagnetic radiation has a linear relationship between the absorbance and concentration (i.e., the Beer–

Lambert–Bouguerre relationship), making it an important analytical tool [32]. The Beer–Lambert–Bouguerre relationship is a main rule in spectrophotometric analysis that gives a great opportunity to find the concentration of a substance by measuring the absorbance of its solution [32].

Organic molecules absorb energy in the near-infrared region when they vibrate or are translated into an absorption spectrum within an NIR spectrometer. At 1300 nm, the NIR region is divided into short-wave NIR (SW-NIR) in the wavelength range of 700 to 1100 nm and standard NIR (780 to 2500 nm). The SW-NIR region is an absorption band of high overtones, whereas the traditional NIR region is an absorption band of the first or second overtone [33][34]. The intensity of absorption decreases as the overtones increase. As a result, SW-NIR is frequently used in transmission analysis, where reflection is significantly reduced so that the amount of radiation attenuated by the sample is measured in transmittance modes, as opposed to standard NIR, which is used in diffuse reflection analysis, which is frequently used for the analysis of opaque solids and is associated with light scattering at the surface to obtain surface information of the samples [35]. Because of the interaction of electromagnetic radiation in the near-infrared region and biological tissues, NIRS has found widespread application in the quantitative evaluation of various crops.

NIRS could be useful for qualitative measurement, but due to the overlapping and non-specific nature of NIR spectra, they become difficult to interpret. However, each peak has enormous hidden information of the molecular bonds absorbing in the respective wavelengths. NIR absorptions between 700 and 1050 nm are usually the second and third overtones of both C-H and O-H bonds, which are mainly for starch and water. Oil has a unique absorption band which appears as a duplet at two characteristic wavelengths of 1700 nm and 2300 nm, while water absorption is at 1925 nm, which is indicative of stretching and bending vibrations of O-H [35]. The combination band of NH at 2130 and 2190 nm is indicative of protein, whereas the first overtones region was the best for predicting starch (1452–1770 nm) [35].

3. Overview of Hyperspectral Imaging Spectroscopy (HSI)

HSI is a modern method which incorporates the critical concept of imaging and spectroscopy and can concurrently obtain spectral and image information from a sample [36][37][38][39][40][41][42]. NIR-HIS was initially used in remote sensing studies but now serves as an emerging technology in various quantitative applications in the food [43][44][45][46], medicine, and agriculture industries [47][48][49]. HSI is a promising method for the rapid and nondestructive sorting and prediction of quality parameters in various root and tuber crop categories, including yam and cassava [21]. NIR-HSI systems can capture a broad range of spectra data from visible to near-infrared and far-infrared regions of electromagnetic radiation. The pixel in the NIR-HSI image has a continuous spectrum of about a hundred bands [50][51][52].

Additionally, the image contains valuable information on the intrinsic chemical compositions and their spatial distributions within the target. HSI has shown the potential to characterize the biochemical and biophysical constituents, including their spatial distribution, simultaneously. Spectral imaging technology is classified as multispectral, hyperspectral, or ultraspectral [19][53].

Hyperspectral images can be generated in various ways, which include a tunable filter, push broom, and whiskbroom, respectively [53]; this depends on the hardware used for the data acquisition. A tunable filter keeps the target fixed and obtains images subsequently from one wavelength to another; this is used when the number of wavelengths needed is limited. ElMasry and Nakauchi, [19] stated that a push broom and whiskbroom rely on scanning the target in the spatial domain by moving the target either line-by-line (push broom) or point-by-point (whiskbroom). Additionally, HSI can be operated in different optical modes, such as reflectance, transmittance, absorbance, or fluorescence, depending on the optical properties of the samples. Most of the published work was performed in the reflectance mode [54][55][56][57]. A "hypercube" is a three-dimensional (3-D) structure obtained with HSI that consists of two spatial and one spectral dimension [58][59]. Because of their ability to combine conventional imaging and spectroscopy, HSI systems can provide physical and geometrical features of the target (i.e., color and appearance) and the chemical composition. As a result, hyperspectral imaging technology has distinct advantages in detecting plant materials' outward and intrinsic quality. It has numerous advantages over traditional analytical methods, including the nondestructive nature of samples and the unrivalled prediction accuracy. It can quickly determine the chemical composition of foods and the spatial distribution of the quality attributes (69).

4. NIR-Hyperspectral Imaging Spectroscopy for Yam and Cassava Food Quality

NIR spectroscopy has recently moved from traditional spectroscopy to coupling with other technologies, including NIR-microscopy, NIR-MIR Spectroscopy, and NIR-Hyperspectral imaging spectroscopy for the quality assessment of root and tuber crops. Along with increased spectra quality from the millions of spectral data points acquired at each wavelength, NIR-HSI also gives information on the spatial distribution of the target product's chemical components. Numerous root and tuber crops, particularly potatoes and sweet potatoes, have been reported to use NIR-HSI for their food quality assessment [26][60][61][62][63][64][65][66][67].

Alamu et al. [18] mentioned in their review paper that only one work characterizing cassava by applying NIR-HIS, that of Su and Sun [68], had been reported at the time of their research. The authors employed the HSI method to identify the adulteration of cassava flour in Irish organic wheat flour (OWF). Between 900 and 1700 nm, hyperspectral images were taken using OWF samples that had different levels of percentage adulterations. For quantitative analysis, PLSR and principal component regression (PCR) were used, and feature wavelengths were chosen using the first derivative and mean centering iteration procedure using the loading plots of PCA (FMCIA). Wavelengths were further decreased following the corresponding feature using the model regression coefficients (RC). The RC-FMCIA-PLSR model produced the best admixture detection outcome for OWF mixed with cassava flour, with R^2_P = 0.973 and RMSEP = 0.036. Khamsopha et al. [69] later reported on another use of NIR-HSI for identifying adulterations of cassava flour in tapioca starch. This investigation added limestone powder to tapioca starch at intervals of 0.5% across a range of 0–100% (wt/wt) to create adulterated tapioca starch. A calibration set of samples (N = 141) and a prediction set of samples (N = 61) were used in the study. All samples were scanned with the NIR-HSI equipment at a wavelength of 935–1720 nm. The model's prediction accuracy was perfect, with a correlation coefficient (R) of 0.99 and a root mean square error of prediction (RMSEP) of 2.47%. Using prediction model visualization techniques, the study demonstrated the potential of NIR-HSI as a quick way for identifying the levels of adulteration in tapioca starch. The application of NIR-HSI for dolomite adulteration in tapioca starch was also evaluated in a different study by the same researchers, who added dolomite in concentrations ranging from 0.5 to 100% (wt/wt). Using NIR-HSI at 935 to 1720 nm, 400 samples of pure and contaminated tapioca starch were scanned. These samples were separated into a calibration set (N = 300) and a validation set (N = 100). For preprocessing, Savitzky–Golay's first derivative differentiation was utilized to create the ideal environment for the classification model. The model's classification of pure and contaminated tapioca was assessed to be 100% accurate [70]. Although there are many practical applications using NIR-HSI for other root and tuber crops, especially potato and sweet potatoes, only a few studies were reported on using NIR-HSI for quality characterization of cassava and yam tubers. A standard operating procedure (SOP) for monitoring water distribution in fresh yam using HSI was reported in the framework of the RTBfoods project. However, this SOP only described the use of HSI to detect the longitudinal distribution of water in fresh roots and tubers using multivariate analysis [71]. Therefore, further SOPs must be developed to investigate the cross-sectional parts of the root and tuber crop for physical and chemical characteristics.

5. Quality Evaluation of Potatoes and Sweet Potatoes with NIR-Hyperspectral Imaging Techniques

The water content and weight of potato tubers was assessed using the hyperspectral imaging technique and artificial neural network algorithms, where 934–997 nm was the wavelength range found to be selective for the absorption band in predicting the water content in the potato tuber [71]. Measurements of the dry matter of potato and sweet potato were conducted using hyperspectral imaging in conjunction with LWPLSR, PLSR, and MLR. Using the MLR model, a highly satisfactory prediction coefficient (R^2P) of 0.96 was obtained [72]. A multispectral real-time system was developed to monitor the moisture content (MC) in dried potato and sweet potato products using near-infrared (NIR) and mid-infrared (MIR) hyperspectral techniques combined with chemometric algorithms. Multivariate models were created using partial least squares regression (PLSR), support vector machine regression (SVMR), locally weighted partial least square regression (LWPLSR), and a back propagation artificial neural network (BPANN) in the full spectral range of 900–10,372 cm^{-1}. The prediction (R^2_P) determination coefficients of 0.950 and 0.904, respectively, were obtained from the simplified SPA-LWPLSR and SPA-BPANN, respectively, indicating good model performances for the tuber MC prediction [73]. Additionally, the NIR hyperspectral technology was used to predict the starch content of sweet potato and potato [74]. The feasibility of hyperspectral imaging systems in monitoring the changes in the moisture (MC) and total anthocyanin (TA) contents of purple sweet potatoes [PSP] during convective hot air drying (CHD) and microwave drying (MD) was investigated [65]. The PLSR model was developed after spectra extraction to predict the TA and MC contents of the processed purple sweet potatoes. For the CHD, a determination coefficient in prediction (R^2p) of 0.836 and 0.817 and a root mean square error (RMSEP) of 0.091 and 0.407 were reported for MC and TA, respectively. However, the R^2p obtained for the MD was 0.831 and 0.766, with an RMSEP of 0.095 and 0.382 for MC and TA, respectively. The authors also established that HSI could be useful for visualizing the distribution of MC and TA during the drying process of the purple sweet potatoes. The authors observed a uniform distribution of MC and TA at the initial drying stage by CHD until after 45 min of drying, when high moisture loss was observed from the core of the sample. They reported that convective hot air drying has better distribution uniformity of the measured parameters than the microwave drying [65]. The starch contents of fresh-cut potatoes were analyzed with hyperspectral imaging techniques using Competitive Adaptive Reweighed Sampling (CARS) and the successive projection algorithm (SPA) to extract characteristic wavelengths from the images. A PLSR model was developed to predict the starch content from the preprocessed full spectrum and the spectrum under the characteristic wavelength. The results indicate that the full spectrum model constructed through standard normal variable transformation (SNV) had the best performance, with a correlation coefficient in the calibration set (Rc) value of 0.9020, a root mean square error of correction (RMSEC) of 2.06, and a residual prediction deviation (RPD) of 2.33 [75].

6. Physical Parameters and Texture Analysis Using Hyperspectral Imaging

Physical parameters such as the color and textural attributes of roots and tubers have become an essential factor driving their final quality at a consumption stage. Consumers' preferences for product quality are influenced mainly by color, particularly when processing substantially impacts product quality [76]. Xiao et al. [77] reported that NIR-HSI was used to determine the color of potatoes. The textural attributes of cassava and yam products, such as boiled and pounded forms, are determined by a sensory evaluation, which may be a subjective and mechanical instrument measurement which requires considerable time [76]. Hyperspectral imaging has been used in evaluating the color and other physical characteristics of other tuber crops, such as potatoes and sweet potatoes [77][78][79][80]. The color of potato slices was observed as they were being air dried using Vis/NIR hyperspectral imaging, and the R^2_P was as high as 0.91 when the PLSR was paired with feature wavelength selection techniques such as chosen interval partial least squares regression (iPLSR) [81]. PLSR was also used to determine the specific gravity and water absorption of sliced potatoes using hyperspectral imaging systems in the NIR spectra range of 900–1700 nm. With the linear weighted principal component regression algorithm, a coefficient of prediction (R^2p) of 0.98 was obtained for specific gravity, and one of 0.97 was obtained for water absorption capacity [82]. The textural characteristics of potatoes and sweet potatoes were assessed during microwave baking using the MIR spectra (600–4000 cm^{-1}); in this research, the LWPLSR performed better than PLSR in determining associated textural qualities such as chewiness, resilience, hardness, gumminess, cohesiveness, and springiness, with a maximum R^2_P value of 0.88 [83]. However, limited literature using it for the textural qualities of cassava and yam exists. Hyperspectral image spectroscopy can potentially support the genetic improvement target for cassava and yam breeding programs by exploring intrinsic quality traits such as color, texture, and selected biochemical parameters. These influence the specific characteristics of root and tuber crops during processing and consumption, with the advantage of nondestructive sampling. NIR-HSI could be adopted as a high throughput method for assessing the food quality of cassava and yam food products. The conventional techniques for texture measurement are destructive to the samples and are sometimes influenced by human factors in the case of the sensory test [84]. However, the hyperspectral imaging technique has found applications in evaluating the textural attributes of potatoes and sweet potatoes [83][85].

7. Limitation of NIR-HSI Spectroscopy

Despite the importance of hyperspectral imaging techniques, it has certain limitations in its applications. NIR-HIS has a vast amount of data, including redundant information that poses challenges during data processing and computational analysis; such massive data require enough storage space for the computer, which adds to the cost of accessories. Second, like conventional spectroscopy, the accuracy of NIR-HSI, an indirect technique, depends on the standard of the reference values; hence, the prediction accuracies depend on the reliability of the wet laboratory analysis. Third, since the strength of imaging resides in its capacity to discern spatial heterogeneity in models, hyperspectral imaging is inappropriate for homogeneous materials such as liquid samples. In addition, providing samples with a high water content, such as fresh foods, results in a strong absorption band in a particular spectral area and obstructs the processing of spectra. Fourth, multicollinearity is another known limitation of hyperspectral imaging. In addition, image pre-processing and modeling could be time-consuming and affected by interferences from instrumental noise and other external factors, such as the ambient condition of the instrument room, which are sometimes challenging to control.

8. Prospects

In the future, researchers should develop more efficient algorithms for data processing and spectral band selection to solve the problem of high dimensionality. Reliable reference values must be obtained for targeted parameters because prediction performances rely on the quality of the reference values. It is imminent that more research on applying NIR-HSI techniques to define and characterize the critical quality parameters for yam and cassava should be conducted. It will contribute significantly to breeding programs to incorporate the priority quality characteristics influencing consumers’ decisions on adopting and utilizing pipeline varieties. Moreover, easy-to-use and accessible software for image processing should be available for research to enhance the handling and processing of spectra and image datasets.

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