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NIR sensors combined with chemometric algorithms in intelligent quality evaluation of sweetpotato roots from 'Farm' to 'Table': Progresses, challenges, trends, and prospects

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ABSTRACT

NIR sensors, in conjunction with advanced chemometric algorithms, have proven to be a powerful and efficient tool for intelligent quality evaluation of sweetpotato roots throughout the entire supply chain. By leveraging NIR data in different wavelength ranges, the physicochemical, nutritional and antioxidant compositions, as well as variety classification of sweetpotato roots during the different stages were adequately evaluated, and all findings involving quantitative and qualitative investigations from the beginning to the present were summarized and analyzed comprehensively. All chemometric algorithms including both linear and nonlinear employed in NIR analysis of sweetpotato roots were introduced in detail and their calibration performances in terms of regression and classification were assessed and discussed. The challenges and limitations of current NIR application in quality evaluation of sweetpotato roots are emphasized. The prospects and trends covering the ongoing advancements in software and hardware are suggested to support the sustainable and efficient sweetpotato processing and utilization.

1. Introduction

Sweetpotato (*Ipomoea batatas*) is a starchy root crop that is widely consumed around the world. It belongs to the Convolvulaceae family and is known for its sweet taste and versatility in cooking. Sweetpotato is believed to have originated in the region that is now part of South

Abbreviations: NIR, Near-infrared; ML, machine learning; AI, artificial intelligence; IoT, internet of things; UAV, unmanned aerial vehicles; VIS, visible; MIR, mid-infrared; SWNIR, short-wave NIR; LWNIR, long-wave NIR; MSC, multiplicative scattering correction; SNV, standard normal variables; DT, de-trending; SGS, Savitzky-Golay smoothing; 1D, 1st Derivative; 2D, 2nd Derivative; BC, baseline correction; NC, normalization correction; PLS, partial least squares; MLR, multiple linear regression; PCR, principal component regression; LDA, linear discrimination analysis; SVM, support vector machine; ANN, artificial neural network; RF, random forest; R^2, coefficient of determination; RMSE, root mean square errors; RPD, ratio of prediction to deviation; PCA, principal component analysis; PC, principal component; UMAP, uniform manifold approximation and projection; SMLR, stepwise multiple linear regression; MPLS, modified partial least squares; SOPLS, sequential orthogonalized partial least squres; LWPLS, locally weighted partial least square; RBF-PLS, radial basis function partial least squares; SVR, support vector regression; RBF, radial basis function; BPANN, Back propagation-artificial neural network; KNN, k-nearest neighbors; DA, discrimination analysis; PLSDA, partial least square discrimination analysis; SVMDA, support vector machine discrimination analysis; R, correlation coefficient; R_P^2, coefficient of determination of prediction; SSC, soluble solid content; RMSEP, root mean square error of prediction; VIS-NIR, visible and near-infrared; RMSECV, root mean square errors of cross-validation; SPA, successive projection algorithm; R_P, correlation coefficient of prediction; SEP, square error of prediction; *T*c, gelatinization completion temperature; *T*o, gelatinization onset temperature; *T*p, gelatinization peak temperature; *T*r, gelatinization temperature range; ΔH, enthalpy of gelatinization; AP, amylose percent; SP, swelling power; AGD, average granule diameter; BGP, big granule percent; MGP, middle granule percent; SGP, small granule percent; RVA, rapid viscosity analyzer; PKV, peak viscosity; HPV, hot paste viscosity; P_{temp}, pasting temperature; CL, cooling loss; CR, cooling resistance; SWD, swelling degree; TVC, total viable counts; $\delta^{13}C$, carbon isotope composition; ABTS, 2,2′-azino-bis(3-ethylbenzothiazoline-6-sulfonic acid) diammonium salts; DPPH, 1,1-diphenyl-2-picrylhydrazyl radical; *G*', storage modulus; *G*", loss modulus; *G**, complex modulus; *K*, consistency index; SIMCA, soft independent modeling of class analogy; FT-NIR, Fourier NIR.

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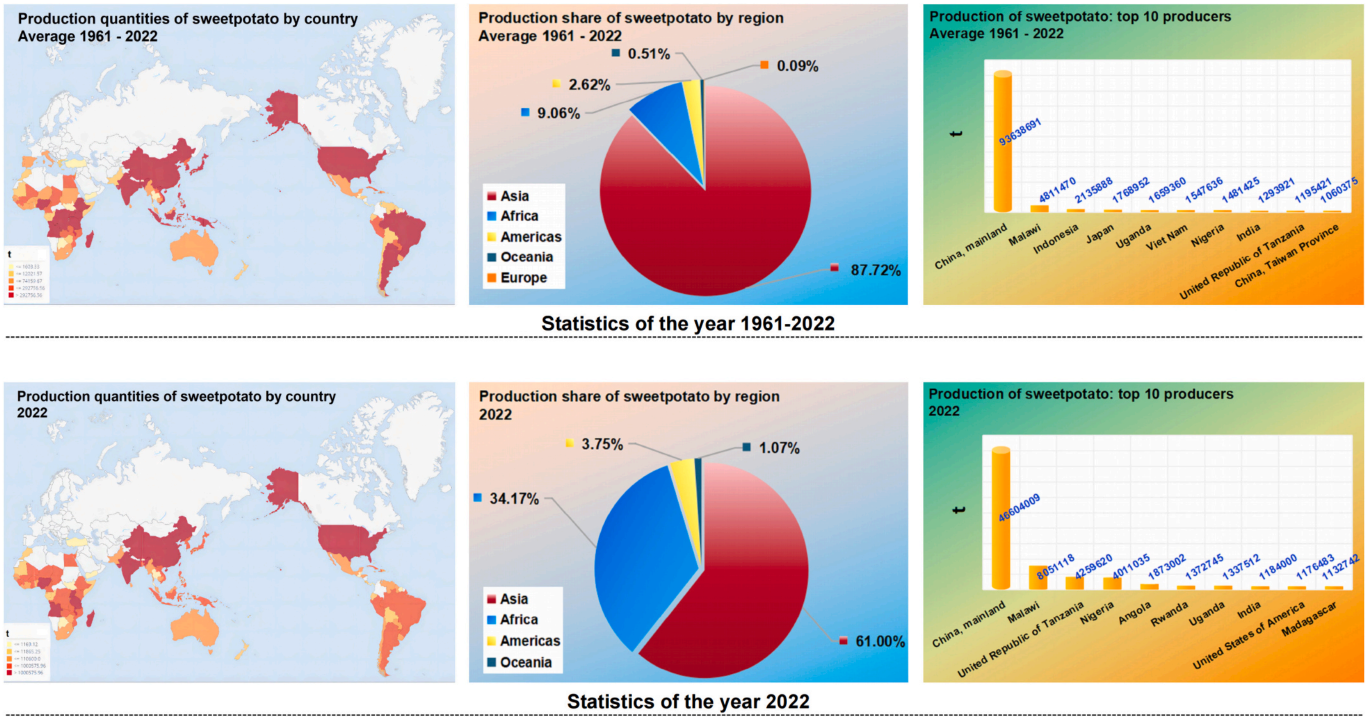

Fig. 1. Statistics of sweetpotato production in different parts of the world from the year 1961–2022, and 2022, respectively.

America, particularly in current Peru and Ecuador. After >5000 years of development, sweetpotatoes has spread to other parts of the world through human migration and trade routes (Mu & Li, 2019). Sweetpotato gained popularity in Europe and were cultivated in botanical gardens for both ornamental and culinary purposes, and then were introduced to Africa and Asia. So far, sweetpotato is cultivated globally and grown in over 100 countries. China leads as the largest producer with 46.6 tons in 2022, followed by other Asian countries with a combined production of 52.71 tons, according to the latest statistical data from Food and Agriculture Organization (FAO), which are shown in Fig. 1. Sweetpotato is well-suited to tropical and subtropical climates, contributing significantly to the food supply in regions like Southeast Asia (Sapakhova et al., 2023). In many developing countries, sweetpotato is a vital component of subsistence farming, playing a crucial role in addressing food shortage issues in part of regions in history, as its nature of cold and drought tolerance, good adaptability to different climates, as well as reliable source of nutrition (Fuglie, 2007).

Sweetpotato is recognized for their nutritional benefits, including high levels of β-carotene, vitamins (mainly vitamin A, and vitamin C), minerals (e.g. potassium), and fiber, which vary in different varieties with orange-, white- and purple-flesh (Padmaja, Sheriff, & Sajeev, 2012). The quality of sweetpotato is affected by several factors, and assessed considering aspects of appearance, texture, flavor, nutritional contents, etc. A pleasing appearance with vibrant skin color and smooth appearance tends to enhance the visual appeal and desire to purchase sweetpotato (Purcell, Walter, & Wilson, 2021). High-quality sweetpotatoes with good texture and flavor will result in more enjoyable and satisfying dishes, therefore leading to better cooking performance (Xu et al., 2023). As the freshly harvested sweetpotato generally has better taste and texture than that stores in an extended period, evaluating the quality of sweetpotato is essential to ensure the optimal flavor during the storage (commonly in a cool and dark environment), maintaining freshness and preventing premature spoilage (van Oirschot, Rees, & Aked, 2003). Identifying any signs of spoilage, including mildew, black spots, sprouting, or off-flavors allows consumer to avoid purchasing potentially spoiled sweetpotato roots (Hedge, Misra, & Jeeva, 2012). In fact, different varieties of sweetpotatoes have varying nutritional profiles, and the ones that meet consumers' nutritional preferences and dietary requirements can be selected by assessing their quality, contributing to the overall health and well-being of human body (Alam, 2021). In addition, the quality of the sweetpotato directly influences the culinary satisfaction when preparing savory dishes, desserts, or snacks (Okello et al., 2021). In summary, evaluating the quality of sweetpotato is crucial for ensuring freshness, flavor, nutritional value, and overall satisfaction in culinary endeavors, enabling to make wise choices that contribute to a positive cooking and dining experience.

Traditional techniques for evaluating the quality of sweetpotato mainly involve visual inspection of external surface features (e.g. skin color, surface texture, wrinkling, size, shape), manual assessment of sensory indicators (e.g. firmness, smell, taste, weight), reagent-based measurement of internal chemical and nutritional components (e.g. moisture, starch, protein, polysaccharides, vitamins, antioxidants, minerals), molecular diagnosis and immunology-based detection of sprouting, virus diseases, microbial spoilage and specific gene, etc. (Karan & Şanli, 2021; Pavithra, Thangamani, Pugalendhi, & Kumar, 2023), which are reliable, effective, and frequently-used, but time-consuming, partly subjective, destructive, and sometimes require well-trained personnel, and specialized equipment to measure. Hence, the development of rapid, non-destructive, real-time analysis technology is crucial for quality assessment of sweetpotato and its products (Sanchez, Hashim, Shamsudin, & Nor, 2020). The necessity and importance of developing such technology for sweetpotato are driven by the need to enhance food safety, maintain quality, reduce waste, comply with regulations, and foster consumer trust in an increasingly complex and interconnected agri-food system (Raki, Aalaila, Taktour, & Peluffo-Ordóñez, 2024).

NIR spectroscopy emerged as a powerful analytical optical technique utilizes the absorption of NIR light by molecular vibrations to provide information about the chemical compositions of samples, and has been widely applied in the agri-food industry for both quantitative and qualitative analysis (Cortés, Blasco, Aleixos, Cubero, & Talens, 2019). Its non-destructive nature, rapid analysis, and ability to provide information about multiple components make NIR an invaluable tool for quality control and process monitoring. With NIR technology, the quality of

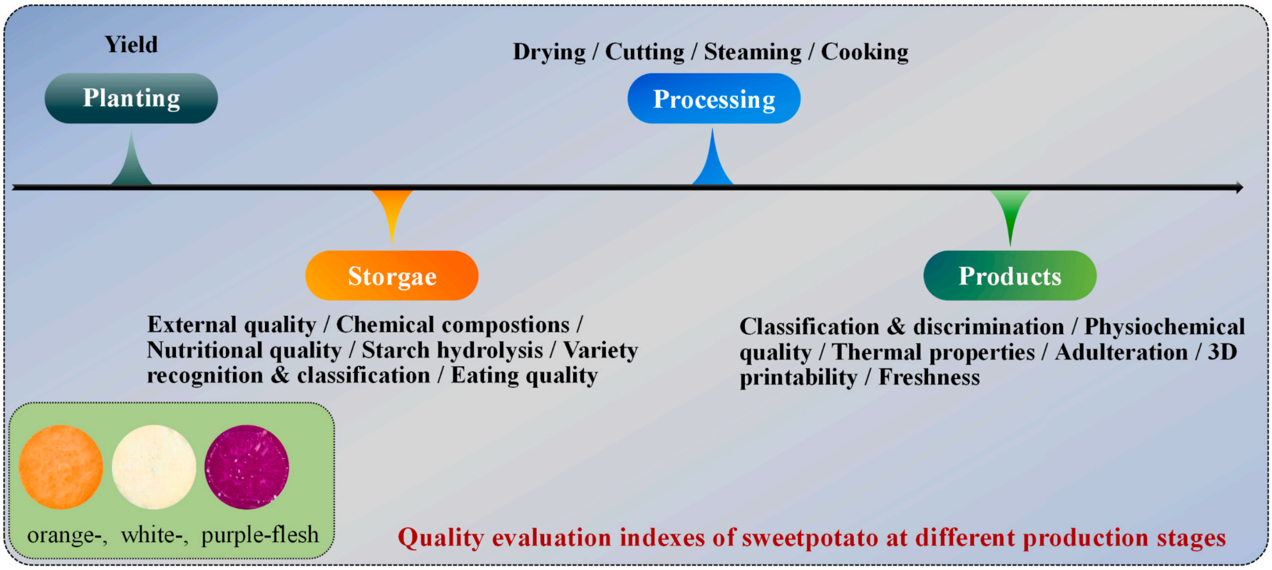

Fig. 2. Graphical exhibition of quality indexes of sweetpotato at different production stages.

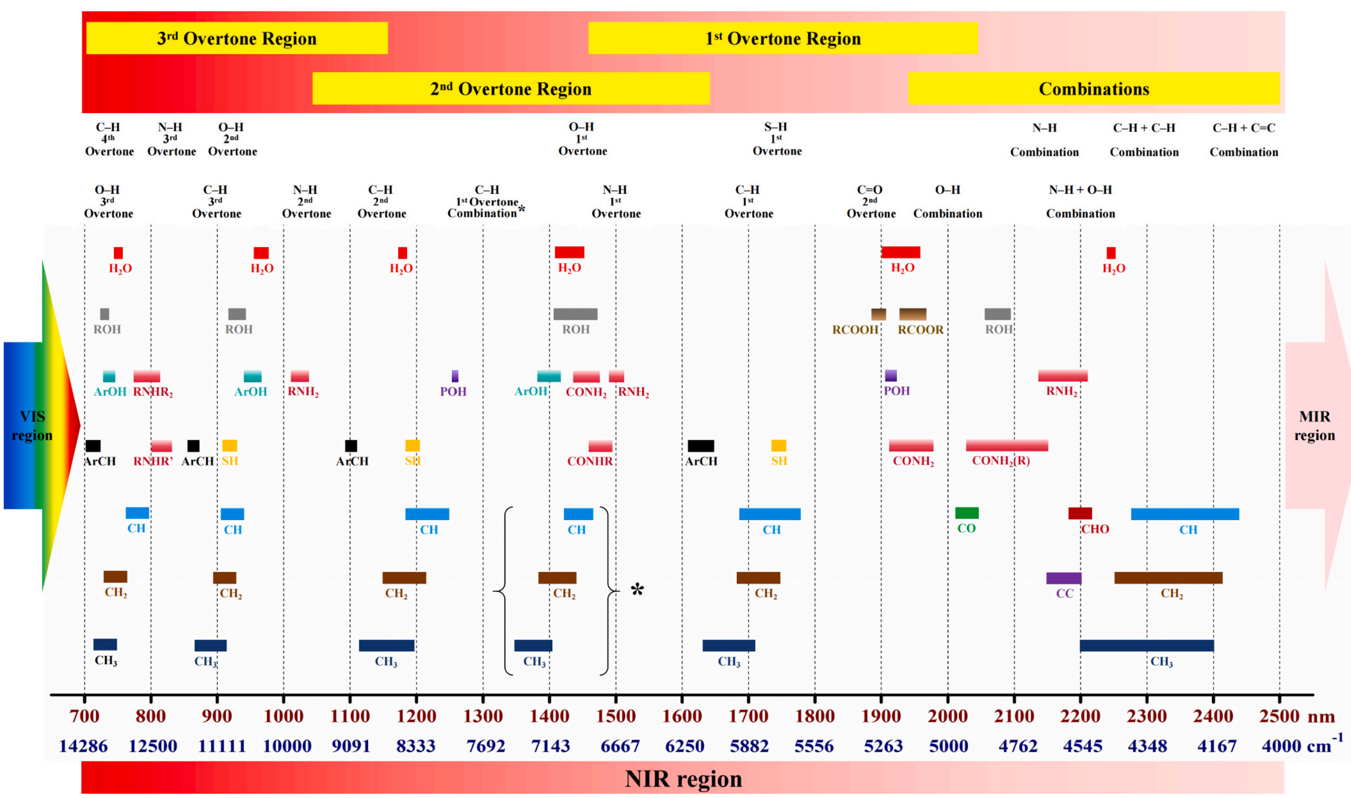

Fig. 3. Diagram of summarized overstones and combinations of fundamental vibrations of chemical bonds in NIR region (Harris & Altaner, 2013).

agri-food can be assessed without altering or damaging the product, allowing for continuous monitoring throughout the production process. Besides, by applying NIR technique, the manufacturers can implement precise process control, optimizing various parameters during production, and leading to improved efficiency, consistency, and overall quality of the final food products (Grassi & Alamprese, 2018). NIR offers a cost-effective alternative, reducing the need for extensive lab testing and associated expenses and is particularly valuable in high-throughput production environments, contributing to faster decision-making and reduced processing time. NIR technology is versatile and has been applied to a wide range of sweetpotato production, from farming to final products. In this review, the wide applications of NIR coupled with chemometrics algorithms to assess sweetpotato quality during different production stages including planting, storage, processing and products are comprehensively summarized, and the specific quality indexes are exhibited in Fig. 2. The capabilities of NIR in both quality prediction and variety classification of sweetpotato are analyzed in detail. The current limitations and challenges of of sweetpotato quality evaluation by NIR are pointed out. The future trends and prospects of developing miniature NIR special equipment for intelligently monitoring sweetpotato quality

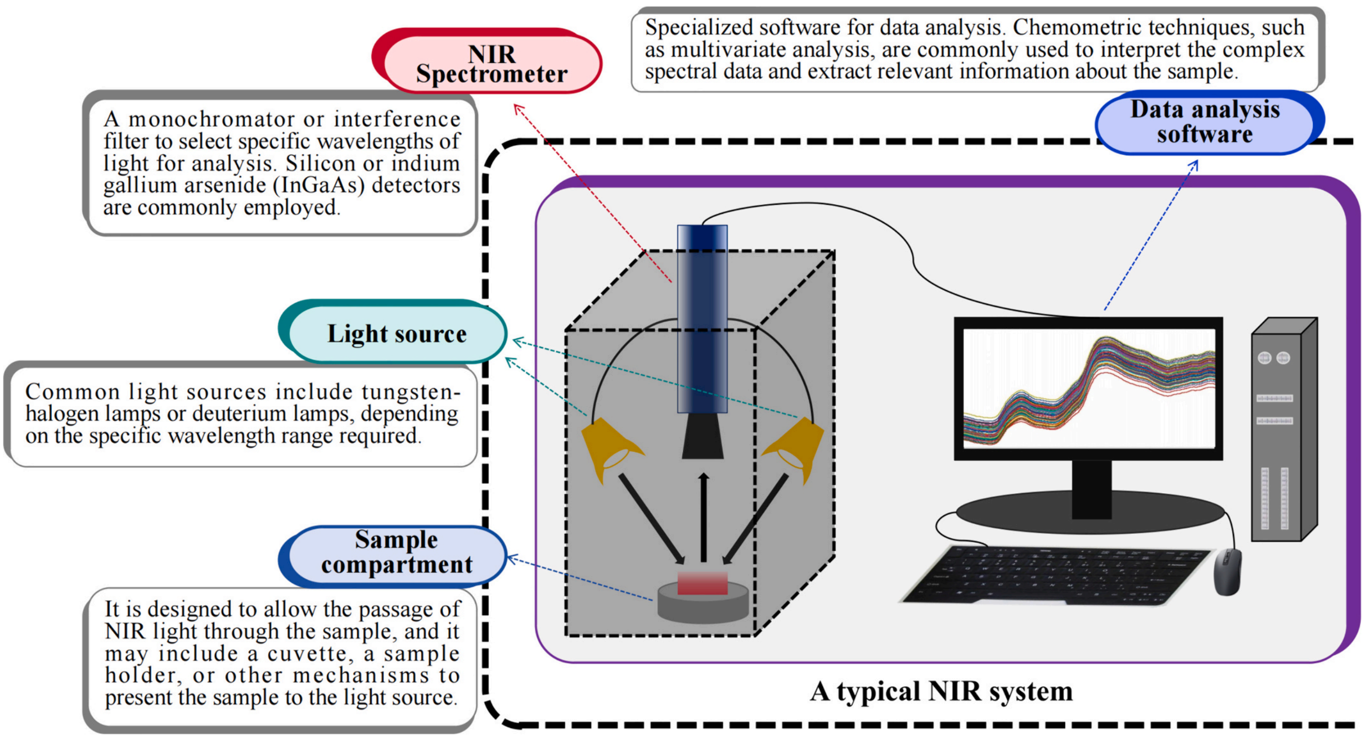

Fig. 4a. Sketch of a typical NIR system containing main components.

are finally put forward, aiming to maximize the industrial application value of NIR in improving efficiency, reducing costs, and ensuring the production and distribution of high-quality sweetpotato in a variety of agricultural settings, as well as promoting sustainability in the food production process.

2. NIR application principle and procedure

NIR, an electromagnetic spectrum between VIS and MIR regions with a wave number of about 4000 to 10,000 cm^{-1}, operates in the 780–2500 nm region to reflect the energy levels associated with overtones and combinations of fundamental vibrations of hydrogen-containing group X–H (X = C, O, N, S) and carbon-containing group (mainly C═C, C═O) in organic compounds of a food sample (Pasquini, 2018). The NIR bands located in different points or intervals can be assigned for 1st overtone, or 2nd overtone, or 3rd overtone, or 4th overtone, or combinations of specific chemical bonds and their distributions are summarized in detail (Workman Jr, 1996), and shown in Fig. 3.

NIR region is typically divided into two regions of SWNIR (780–1100 nm) and LWNIR (1100–2500 nm). SWNIR is commonly used

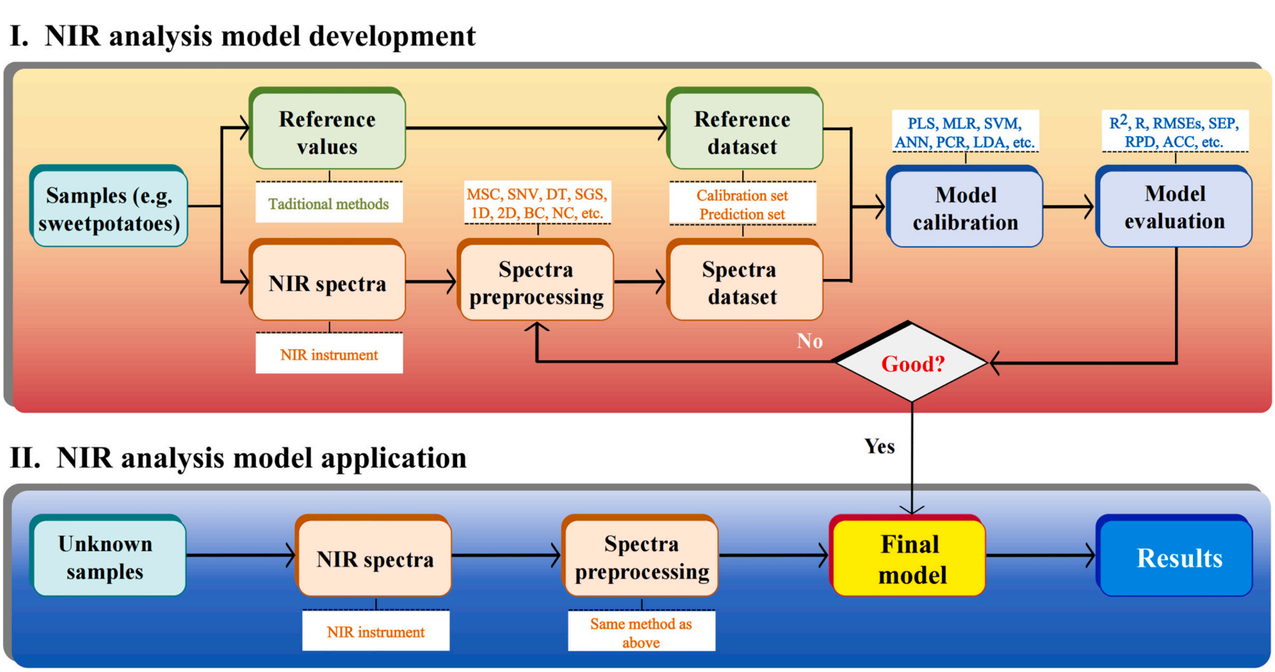

Fig. 4b. Flow chart of NIR analysis procedures.

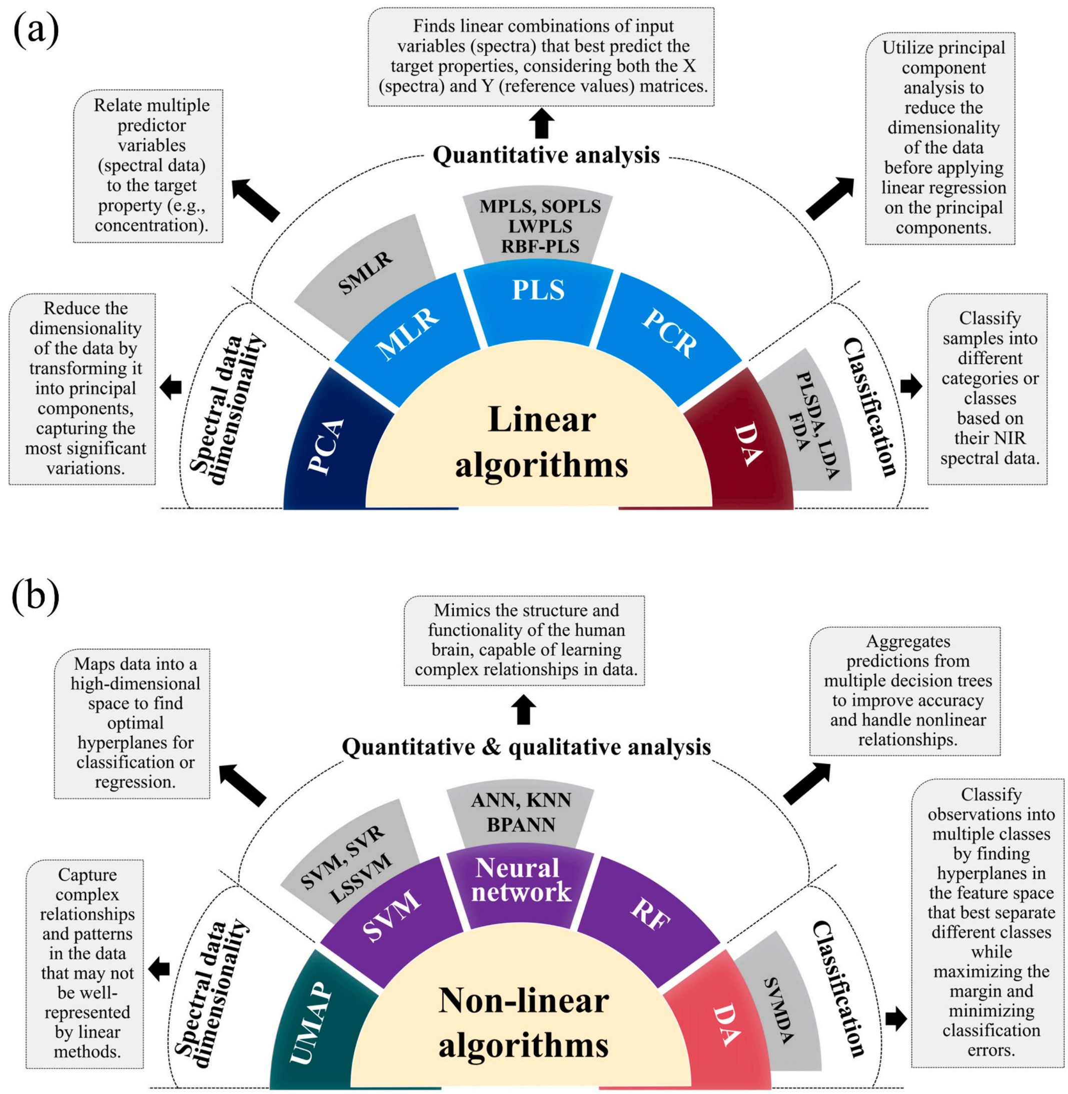

Fig. 5. Summary diagram of chemometric algorithms in NIR analysis of sweetpotato roots.

for routine quantitative analysis of main components in samples including moisture, fat, protein, carbohydrates, and other constituents in agri-food products, due to its strong sensitivity to overtones of fundamental vibrations of common chemical bonds, particularly those involving H, C, O, and N (Ma, Babu, & Amamcharla, 2019). SWNIR is advantageous for its ability to quickly analyze major components in samples without the need for extensive sample preparation, making it suitable for high-throughput applications (Ge et al., 2019). LWNIR is frequently employed for the identification of specific compounds, detection of chemical groups, and more detailed characterization of samples, as it is sensitive to more complex overtones and combinations of fundamental vibrations of chemical bonds. In the agri-food industry, LWNIR can be used for the in-depth analysis of the chemical compositions of food products, including the identification of specific compounds related to flavor, aroma, and nutritional content (Hussain et al., 2023), and is suitable for in-line and at-line process monitoring, providing real-time insights into the chemical changes during food processing (Dixit et al., 2017). The choice between SWNIR and LWNIR depends on the specific analytical requirements and the nature of the sample being analyzed. In practice, many NIR instruments cover both SWNIR and LWNIR ranges, allowing for a broader range of applications and versatility in analytical methods. The main components of a typical NIR system is shown in Fig. 4a.

NIR analysis is versatile and can be applied to various agri-food parameters, including moisture, protein, fat, fiber, and more. The key to successful NIR analysis lies in the careful development and validation of calibration models based on the specific characteristics of the agri-food products (Vincent & Dardenne, 2021). The whole detailed procedures of NIR analysis in agri-food products (e.g. sweetpotato) are shown in Fig. 4b, mainly including NIR analysis model development and application. Among, a representative set of samples that cover the expected variability are required and should be prepared appropriately by considering the form of the material (solid, liquid, or powder). After illuminating the samples by NIR light, the reflectance or absorbance spectra can be collected and commonly preprocessed by various methods, including baseline correction, smoothing, normalization, and derivative transformations (e.g. MSC, SNV, DT, SGS, 1D, 2D, BC, NC, etc.) (Jiao, Li, Chen, & Fei, 2020). Chemometric analysis, linear regression (e.g. PLS, MLR, PCR, LDA, etc.) or nonlinear operation (e.g. SVM, ANN, RF, etc.), are then utilized to mine the NIR spectral features, correlating the preprocessed NIR spectra with the reference values, i.e. modeling. By evaluating the model performance, considering several parameters including R, R^2, RMSE, RPD, etc., the final best model is selected and applied in the analysis of unknown samples. In a word, NIR is a powerful tool that can be tailored for either quantitative or qualitative analysis based on the specific goals and requirements of the application.

3. Chemometric algorithms for NIR analysis

Various chemometric algorithms have been used for NIR analysis and are key components to enable as much useful information as possible to be obtained from the spectrum, thereby improving the robustness and accuracy of the analytical results, including linear and nonlinear. These algorithms are used in chemometrics, which is the application of statistical and mathematical methods to analyze chemical data. Choosing between linear and nonlinear algorithms depends on the complexity of the relationships in the data. Linear algorithms may be sufficient for simpler relationships (Wang et al., 2022), while nonlinear algorithms can capture more intricate patterns (Zareef et al., 2020). In practice, a combination of linear and nonlinear algorithms may be employed to ensure the flexibility needed for accurate calibration and prediction in NIR analysis. The choice often involves a trade-off between interpretability and model complexity. The algorithms used in NIR analysis of sweetpotato are outlined and exhibited in Fig. 5. Among, linear algorithms in NIR analysis are commonly used for calibration and modeling to establish relationships between the NIR spectra and the properties of sweetpotato in a linear fashion. Non-linear algorithms are employed in NIR analysis when the relationships between the spectra and the properties of sweetpotato are complex and cannot be adequately modeled by linear methods.

3.1. Data dimensionality reduction algorithms

NIR analysis often involves high-dimensional spectral data, where each data point corresponds to a spectrum recorded over a range of wavelengths. To handle the challenges of high-dimensional data and improve model performance, dimensionality reduction techniques are commonly employed (Li, Li, Yang, & He, 2021). For the sweetpotato quality evaluation by NIR sensors, two techniques including PCA (Fig. 5a) and UMAP (Fig. 5b) are frequently used to reduce the dimensionality of NIR spectral data.

PCA aims to transform the original high-dimensional spectral data into a new set of uncorrelated variables, i.e. PCs, ordered by the amount of captured variance (Beattie & Esmonde-White, 2021). The amount of variance can be explained by each PC whose contribution is visualized in a scree plot or cumulative variance plot (represented as PC score). PCA in NIR analysis is a valuable tool for exploratory data analysis, noise reduction, and dimensionality reduction, helping identify relevant spectral features and facilitates the development of models for various applications (Bruni, Cardinali, & Vitulano, 2022). Unlike PCA, UMAP can capture non-linear relationships in the data, and is particularly beneficial in NIR analysis (Vermeulen, Smith, Eremin, Rayner, & Walton, 2021). UMAP aims to represent high-dimensional data in a lower-dimensional space, typically 2D or 3D, and to maintain the intrinsic relationships present in the original data at the same time. UMAP emphasizes the preservation of both local and global structures in the data, by keeping nearby points close to each other in the low-dimensional level, preserving the local relationships, while also capturing the global structure. UMAP is often employed for visual exploration of spectral datasets, revealing clusters, patterns, and outliers in data that might be challenging to observe in the original high-dimensional space. UMAP is becoming increasingly popular for visualizing high-dimensional data in a lower-dimensional space and has potential applications in NIR analysis (Guo et al., 2024).

3.2. Quantitative and qualitative analysis algorithms

Quantitative analysis in NIR spectroscopy involves predicting the concentration or content of specific compounds or properties in a sample based on its NIR spectral data. Various algorithms and are employed for quantitative analysis in NIR, and the choice often depends on the nature of the data and the specific requirements of the analysis. Some quantitative algorithms, involving linear and non-linear, have been applied in the quality evaluation of sweetpotato and are shown in Fig. 5.

MLR is a straightforward and interpretable method used in NIR analysis when the relationships between spectral features and target variables are primarily linear, offering a useful baseline model for comparison with more complex algorithms. It assumes a linear combination of the predictor variables, and estimates coefficients to best fit the observed values of the target variable (e.g., reducing sugar content in sweetpotato) (He et al., 2022). MLR can be expressed as $Y = a_0 + a_1X_1 + a_2X_2 + \bullet\bullet\bullet + a_nX_n + \varepsilon$ (Y is target variable; a_0 is intercept; a_1, •••, a_n are coefficients; ε is error term). SMLR is sometimes employed in NIR analysis for building regression models through selecting the most relevant subset of predictor variables (wavelengths in the NIR spectrum) that contribute significantly to the prediction of the target variable (e.g., polysaccharide concentration in sweetpotato) (Xiao et al., 2022). PLS is a widely regression-based multivariate statistical technique in NIR analysis for modeling the relationship between NIR data and a response variable (e.g., dry matter concentrations in sweetpotato) (Kamruzzaman & Villordon, 2022). It is particularly useful when dealing with high-dimensional data and situations where there is multicollinearity and high dimensionality in NIR data, allowing for the extraction of LVs that capture the most relevant information by maximizing the covariance between the NIR data and the response variable (Bjørsvik & Martens, 2007). PLS model can be expressed as $Y = b_0 + b_1X'_1 + b_2X'_2 + \bullet\bullet\bullet + b_mX'_m + \varepsilon'$ (Y is response variable; b_0 is intercept; b_1, •••, b_m are coefficients; ε' is error term). PCR combines PCA for data dimensionality reduction with MLR to predict the target variable (e.g., rheological parameters in sweetpotato) (Chen, Zhang, Devahastin, & Yu, 2021). PCR can be expressed as $Y = c_0 + c_1PC_1 + c_2PC_2 + \bullet\bullet\bullet + c_kPC_k + \varepsilon''$ (Y is response variable; c_0 is intercept; c_1,•••, c_k are coefficients; PC_1, •••, PC_k are retained PCs, ε'' is error term). MPLS, SOPLS, LWPLS and RBF-PLS are extensions or derivative versions of traditional PLS algorithm to enhance the capabilities in dealing with complex datasets (Font, del Río-Celestino, Luna, Gil, & de Haro-Bailón, 2021; Lesnoff, Metz, & Roger, 2020).

SVM is a machine learning algorithm that can be applied to NIR data for various analytical purposes, including regression and classification tasks (Devos, Ruckebusch, Durand, Duponchel, & Huvenne, 2009). It is known for its ability to handle high-dimensional data and nonlinear relationships effectively. SVR regression is applied when the goal is to predict a continuous variable, such as the concentration of a particular compound (e.g. SSC in sweetpotato) (Shao et al., 2020), based on NIR spectra. Kernel functions embedded in SVM algorithm are used to capture complex relationships between the NIR spectra and the target variable (Chen et al., 2020). SVM classification is used when the goal is to classify samples into different predefined classes based on their NIR spectra. It often uses kernel functions (mainly refers to RBF) to implicitly map the input data into a higher-dimensional space, making it possible to find a hyperplane that separates classes. The choice of kernel function can impact SVM performance and its selection may depend on the nature of the data and the problem at hand (Savas & Dovis, 2019). In short, SVM is powerful in NIR analysis, providing robust models for both quantitative and qualitative measurements. The good ability to handle high-dimensional data and nonlinear relationships makes SVM suitable for extracting meaningful information from complex NIR spectra. ANN, a type of machine learning model inspired by the structure and functioning of the human brain, can be applied for NIR analysis by designing an architecture of neural network including the number of layers, nodes in each layer, and the activation functions, and that may vary based on the specific task (regression, classification, and pattern recognition) (Jernelv, Hjelme, Matsuura, & Aksnes, 2020). The trained network can be used to predict concentrations using new spectra (e.g. moisture in sweetpotato) (Su, Bakalis, & Sun, 2020), and classify new spectra into the appropriate classes. In addition, by training an unsupervised or self-organizing ANN to learn patterns within the NIR data without explicit class labels, the ANN can be used to identify deviations from learned patterns (Makmuang et al., 2023). It should be noted that it's essential to carefully design and train the network in NIR analysis, considering the specific requirements of the analysis task. BPANN specifically refers to an ANN trained using the backpropagation algorithm, and is a supervised learning algorithm where the network learns from labeled data by adjusting its weights to minimize the error between predicted and actual outputs (Wang, Lin, & Dang, 2020). BPANN may excel in capturing intricate patterns in high-dimensional data but might require more computational resources for training. KNN, a different approach compared to ANN, is a simple, non-parametric, and instance-based learning algorithm, achieving predictions based on the majority class (for classification) or average (for regression) of the k-nearest data points in the feature space (Boateng, Otoo, & Abaye, 2020). Unlike ANN, KNN doesn't learn a model during a training phase. Instead, KNN stores the entire training dataset and makes predictions based on the proximity of new data points to existing points in the feature space. KNN can be computationally intensive during prediction, especially with large datasets, but it's simple and effective in low-dimensional spaces. Both BPANN and KNN can be used for classification and regression tasks (e.g. variety classification of sweetpotato) (Ding, Ni, & Kokot, 2015), but represent different philosophies in machine learning. RF, a popular ensemble learning algorithm, belongs to the family of decision tree-based methods and is known for its robustness and versatility (Savargiv, Masoumi, & Keyvanpour, 2022). It also can be applied to NIR analysis for both classification and regression (e.g. total flavonoid content in sweetpotato) (Tang et al., 2023). By training a RF regressor or a classifier using the labeled NIR dataset, multiple decision trees are built during the training process to make prediction. RF provides a measure of feature importance, indicating the contribution of each NIR wavelength to the overall prediction, which is valuable for feature selection and interpretation. The ensemble nature of RF helps mitigate overfitting and can improve the model's generalization to new data. The ability to handle high-dimensional data and capture complex relationships makes RF well-suited for the analysis of spectral data (Ayesha, Hanif, & Talib, 2020).

3.3. Classification algorithms

Classification algorithms can be applied to NIR analysis to categorize samples into predefined classes based on their spectral data. A few DA algorithms are used in NIR analysis for sweetpotato discrimination between different classes or groups, aiming to find the combination of variables (e.g. wavelengths in NIR spectra) that maximizes the separation between classes (Zeng et al., 2021).

LDA calculates the mean and covariance matrix for each class to find the linear discriminant function coefficients that maximize the ratio of between-class variance to within-class variance (Safo & Ahn, 2016). It constructs a linear decision boundary, or discriminant function, that maximizes the separation between different classes in the feature space. The primary objective of LDA in NIR analysis is to classify samples into different categories or classes based on their NIR spectral data (e.g. classification of healthy and defective sweetpotato) (Shao et al., 2022). PLSDA is a multivariate statistical method commonly used in NIR analysis, specifically for classification tasks (e.g. discrimination and grading of sweetpotato) (Su & Sun, 2016). It combines elements of PLS regression and DA to model the relationship between NIR spectra and class membership, and is particularly useful when dealing with high-dimensional and collinear data, such as spectral data in the NIR range (Lee, Liong, & Jemain, 2018). SVMDA is an approach that combines the principles of SVM with those of DA for classification tasks, aiming to find a decision boundary that maximally separates different classes in the feature space, which makes SVMDA suitable for classifying samples based on NIR data (e.g. adulteration of sweetpotato flour) (Chen, Gao, Ye, Lei, & Zhao, 2019). SVMDA is powerful for classification purposes in NIR analysis, especially when dealing with non-linear relationships in high-dimensional data (Marcelo et al., 2019). Proper hyperparameter tuning and careful consideration of kernel choices contribute to its effectiveness (Guido, Groccia, & Conforti, 2023).

4. Applications of NIR for sweetpotato quality evaluation at different stages

4.1. Planting stage

Yield is a crucial factor in the quality evaluation of sweetpotato and is often considered an important parameter in assessing the overall productivity and economic value of the crop (Alam et al., 2024). Farmers, researchers, and policymakers often consider yield as a key parameter when assessing the success of sweetpotato cultivation (Mukhopadhyay, Chattopadhyay, Chakraborty, & Bhattacharya, 2011). The rapid evaluation of sweetpotato yield at the planting stage provides farmers with timely information to make proactive decisions, optimize resource use, and mitigate potential risks, contributing to the overall success and efficiency of sweetpotato cultivation throughout the growing season. Tedesco, de Almeida Moreira, Júnior, Papa, and da Silva (2021) downloaded high-resolution remote sensing satellite images, and analyzed the spectral changes of canopy containing 785–900 nm bands to accurately predict the yield of sweetpotato in summer and winter fields based on the three market class of roots (Extra A $>$ 0.45 kg, 0.15 $\leq$ Extra AA $\leq$0.45 kg, Extra $<$0.15 kg), providing a timely insight on sweetpotato yield prediction and broadening horizon for harvesting high-quality sweetpotato roots.

At present, there are no specific NIR sensors designed specifically for the yield prediction of sweetpotato roots. Employing existing technology for this purpose is a common option in precision agriculture. Collaboration with experts, researchers, and equipment manufacturers in agriculture may be beneficial to explore the development of specialized solutions by NIR sensors in the future.

4.2. Storage stage

The storage quality of sweetpotato roots is crucial for maintaining their nutritional value, taste, and overall marketability throughout the storage period (Zhou, Chen, Chen, Li, & Yang, 2021). Evaluating sweetpotato root storage quality involves monitoring and controlling the changes of sensory, physicochemical and nutritional attributes, as well as variety classification. NIR is important for the storage quality evaluation of sweetpotato roots due to its non-destructive nature, rapid analysis, ability to assess multiple parameters, predictive capabilities, suitability for process monitoring, consideration of varietal differences, support for quality control in the supply chain, and cost-effectiveness.

4.2.1. Sensory quality

The external sensory quality of sweetpotato roots is critical for determining their market value and consumer acceptance. Several factors (e.g. firmness) can influence the external quality of sweetpotato roots during storage, which should be monitored to ensure a high-quality product. Firmness is a key indicator of textural quality and can influence consumer satisfaction of sweetpotato roots (Nakatumba-Nabende et al., 2023). Based on the full range spectra (400–1000 nm), the firmness of three varieties of sweetpotato storage roots were evaluated with good accuracy achieved from full SNV spectra-based SVR model ($R_P^2 = 0.93$), but reduced one from nine feature wavelengths-based MLR model ($R_P^2 = 0.79$) (Ahmed, Lu, Villordon, & Kamruzzaman, 2023), which is probably because of elimination of some important spectral information relevant to firmness prediction during the RFE process for wavelength selection, thus weakening the prediction effect.

4.2.2. Physicochemical and nutritional quality

The sweetpotato root is composed of various physical, chemical and nutritional components. Understanding the physical and chemical components of sweetpotato roots is essential for assessing their nutritional value and culinary uses. The nutritional profile of sweetpotatoes makes them a valuable addition to a balanced diet, providing a mix of energy, vitamins, minerals, and antioxidants (Amagloh, Yada, Tumuhimbise, Amagloh, & Kaaya, 2021). The specific composition can vary among different varieties and growing conditions. Among, moisture is a major component of sweetpotato roots, contributing to their overall weight and succulence. However, excessive moisture on the surface can cause decay and the growth of mold. Moisture content is a critical factor in evaluating the storage quality of sweetpotato roots (Abrham, Beshir, & Haile, 2021). Proper control and monitoring of moisture levels are essential to prevent various storage-related issues and maintain the overall quality of sweetpotato roots. Dry matter represents the portion of the root that remains after the removal of water and is a key indicator of the composition and overall quality of sweetpotato roots. The importance of dry matter for sweetpotato root quality evaluation during storage lies in its association with texture, starch and sugar content, nutrient density, postharvest changes, water content, shelf life, storage duration, and suitability for culinary use and processing (Zhang, Wheatley, & Corke, 2002). While protein content is not typically the primary indicator in evaluating sweetpotato root quality, it can indirectly impact certain aspects of storage and overall quality (Laurie, Naidoo, Magwaza, Shimelis, & Laing, 2020). Starch is a crucial component in sweetpotato roots and serves as the primary storage carbohydrate. Monitoring starch levels helps in making wise decisions regarding storage conditions, postharvest changes, and the overall quality of sweetpotato roots for both fresh consumption and processing (Guo et al., 2019). Besides starch, sweetpotato roots contain sugars, including sucrose, fructose, glucose, and maltose, influencing the overall sweetness flavor, and overall quality of roots (Shen, Xiang, Wu, Li, & Luo, 2021). Cellulose contributes to the structural integrity of sweetpotato cells and increases the overall fiber content (de Albuquerque, Sampaio, & de Souza, 2019). The antioxidant components including anthocyanins, phenolic compounds, and flavonoids in sweetpotato roots help preserve the color, flavor, nutritional value, and overall quality (Tang et al., 2019). These antioxidants contribute significantly to the root's ability to withstand storage-related challenges and maintain high-quality standards. Minerals are essential for the growth, development, and overall quality of sweetpotato roots. Adequate mineral levels contribute to the maintenance of root quality, including texture, color, and overall marketability (Dos Santos et al., 2019).

All these quality indicators during the period of sweetpotato roots storage were investigated by NIR analysis and a rapid and reagent-independent approach was expected to be developed as a alternative tool, and the specific results are summarized and shown in Appendix. Through comparative analysis, it was observed that the vast majority of indicators of sweetpotato roots were well evaluated by linear calibration algorithms (PLS & MLR) with R_P^2 larger than 0.80 (Magwaza, Naidoo, Laurie, Laing, & Shimelis, 2016; Su & Sun, 2017a; Bu, Li, & Yan, 2018; Bu et al., 2018; Tian, Huang, Bai, Lv, & Sun, 2019; Tian et al., 2021; He et al., 2022; Xiao et al., 2022; He et al., 2023; Tang et al., 2023; He et al., 2023; He et al., 2023), while the maltose, cellulose, and minerals were poorly predicted (Amankwaah et al., 2023; Lebot, Malapa, & Jung, 2013; Lebot, Ndiaye, & Malapa, 2011), which may due to the very small amounts of the three substances, as NIR sensor typically performs better in predicting substances with higher contents (Porep, Kammerer, & Carle, 2015). In a few studies, only calibration datasets were applied for modeling, while no prediction datasets were provided, which meant that the reliability and robustness of the results had not been further verified (Kamruzzaman & Villordon, 2022; Tang et al., 2013; Tang, Li, & Ma, 2008). Based on the spectral data of 400–1000 nm range, SVR algorithm allowed for the better performance in predicting SSC with 18 feature wavelengths ($R_P^2 = 0.8581$, RMSEP $= 0.2951$°Brix, RPD $= 2.56$), than MLR algorithm with 36 ones ($R_P^2 = 0.8153$, RMSEP $= 0.2744$°Brix, RPD $= 2.09$) (Shao et al., 2020), for two different sweetpotato cultivars. By measuring the spectral variations within the full 760–1420 nm range, the starch hydrolysis process of sweetpotato roots were assessed via the estimation of moisture and starch contents (Kim, Choi, & Shin, 2021). The ripening viscosity (expressed by peak torque) and sweetness (expressed by soluble sugar) were also determined by VIS-NIR (350–1100 nm) to evaluate the eating quality of sweetpotato roots (Bu, Li, & Yan, 2018; Bu, Peng, et al., 2018).

In general, NIR performed well in monitoring various physicochemical and nutritional quality indicators of sweetpotato roots during the storage except cellulose. Implementing NIR technology during storage allows for real-time insights into the quality of sweetpotato roots, enabling timely interventions and optimization of storage conditions to preserve nutritional quality and market appeal.

4.2.3. Variety recognition and classification

Variety recognition and classification are essential components of sweetpotato roots quality evaluation during storage, playing a significant role in ensuring consistency, marketability, and consumer satisfaction (Qin, Naumovski, Ranadheera, & D'Cunha, 2022). Implementing effective variety-specific grading systems enhances the overall quality management of sweetpotato roots throughout the storage and marketing process. NIR contributes to the precision and efficiency of quality evaluation processes, supporting optimal storage conditions and ensuring that sweetpotato roots of different varieties meet market demands.

Based on three different levels of moisture content (40–59%, 60–73%, 76–84%), the sweetpotato storage roots cultivars originated from USA, UK, Ireland and Egypt were recognized by mining the 944–1678 nm range data using supervised PLSDA algorithm, allowing for the 6 selected wavelengths to generate R_{CV}^2 from 0.917 to 0.989, and RMSECV of 0.049–0.136%, as well as overall 0 classification error for all the three levels (Su & Sun, 2016), which revealed a good potential of NIR in variety recognition of sweetpotato roots. By applying the same PLSDA analysis, a 100% overall classification accuracy was also obtained with the eight wavelengths selected from same spectral range (Su & Sun, 2017b), five wavelengths selected from 964 to 1645 nm (Su, Bakalis, & Sun, 2019), and five wavelengths selected from 400 to 1000 nm (Kamruzzaman & Villordon, 2022). However, the four studies did not provide an independent samples sets for prediction. More investigations should be conducted to further verify the model effectiveness and reliability. The healthy and defective (frostbitten and diseased) of sweetpotato storage roots were accurately discriminated by executing LDA algorithm, resulting in 99.52% accuracy in prediction for either ten wavelengths selected by SPA, or ten wavelengths selected by RF (Shao et al., 2022), which provides a feasible ideas for the automatic NIR-based classification of stored sweetpotato roots.

In summary, NIR is important for sweetpotato root quality evaluation during storage and provides valuable insights into key quality parameters, facilitating real-time monitoring, process control, and informed decision-making to maintain optimal storage conditions and preserve the quality of sweetpotato roots.

4.3. Processing stage

Sweetpotato roots processing involves various methods (e.g. drying, cutting, steaming, cooking, etc.) to convert raw sweetpotato roots into a range of products for consumption or industrial use. The processing help not only add value to the sweet potatoes roots but also offer a diverse range of products for consumers, contributing to food security and economic opportunities for farmers and food processors (Mu, Sun, Zhang, & Wang, 2017). The choice of specific processing method depends on the desired end product and market demand.

During the processing stage, NIR can be used for quality control of sweetpotato. For example, the earliest research on starch, moisture, and sugar content prediction of sliced fresh sweetpotato roots was reported by Katayama, Komaki, and Tamiya (1996). Calibrated MLR model based on three years of NIR data (680–1235 nm) predicted starch and moisture content in slices adequately ($R_P \geq 0.930$, SEP ≤ 2.00%), but sugar weakly, which may be due to the narrow spectral information involved in analysis. After cooking by a microwave oven, the cooking loss of sweetpotato roots was well-predicted by a full 964–1645 nm range spectra-based PLS model ($R_P^2 = 0.951$, RMSEP = 0.049). The selected five wavelengths improved the prediction efficiency while reduced the accuracy obviously ($R_P^2 = 0.913$, RMSEP = 0.058) (Su et al., 2019). During drying process, the moisture was quantified with excellent performance observed by applying PLS and BPANN ($R_P^2 > 0.95$) based on either full range spectra or selected optimal wavelengths (Heo, Choi, Kim, & Moon, 2021; Su et al., 2020), significantly better than using MLR and SVM algorithm (Peng et al., 2021; Sun et al., 2017). It was indicated that LWNIR spectra was more suitable for moisture prediction than SWNIR spectra, which may due to the presence of more functional groups related to water absorption in the LWNIR region. According to the dryness degree, the purple-flesh sweetpotato were discriminated with overall accuracy of >80% (Heo et al., 2021). In addition, considering SWNIR data (400–1050 nm), the anthocyanin content in purple-flesh sweetpotato slices during drying process was estimated with satisfying results ($0.86 < R_P^2 < 0.90$, RMSEP≦0.302 mg/g) (Liu et al., 2017; Peng et al., 2021), allowing for the slight better performance from SVM prediction than from MLR calculation, which meant that there may be more nonlinear relationships between NIR data and anthocyanin concentration than linear ones.

By comparison, it was observed that moisture was one of the most studied quality parameters used for quality evaluation of sweetpotato roots at the processing stage, and its prediction effect based on NIR technique was better than other indexes (starch, sugar, anthocyanin). Less than nine wavelengths were selected for improving PLS model efficiency in moisture prediction, which provides a new perspective of developing simple equipments for rapid and real-time spot investigation. Overall, the NIR technique performed good in both prediction of chemical compositions and classification purpose at the processing stage. The dynamic changes of other quality indicators of sweetpotato roots during the processing based on NIR sensors should be studied to enhance the universality and applicability of NIR technology.

4.4. Product stage

Sweetpotato roots can be processed into a variety of products (e.g. starch, flour, noodle) that cater to different tastes, dietary preferences, and culinary applications, contributing to the overall popularity and marketability of sweetpotato in various food industries (Al-Maqtari et al., 2023; Bach, Bedin, Lacerda, Nogueira, & Demiate, 2021). The use of NIR spectroscopy in the quality evaluation of processed sweet potato products offers advantages such as speed, non-destructiveness, and the ability to analyze multiple parameters simultaneously.

The thermal properties of sweetpotato starch was initially analyzed by mining LWNIR data (1100–2500 nm) in terms of *T*c, *T*o, *T*p, *T*r and *ΔH* and gave the good MPLS modeling performance ($R_P^2 = 0.838$–0.889) (Lu, Huang, & Zhang, 2006a). With the same range of NIR information and the same data analysis algorithm, the physiochemical qualities (amylose, AP, starch, protein, phosphorus, solubility, SP) and pasting properties (granule property: AGD, BGP, MGP, SGP, crystallinity; RVA property: PKV, HPV, breakdown, setback, P_{temp}) of sweetpotato starch were measured with high R_P^2 values of 0.815–0.917 for all these parameters except MGP (Lu, Huang, & Zhang, 2006b). The two investigations showed the sufficient accuracy and effectiveness of NIR technique in rapid evaluation of sweetpotato starch. Large numbers of new sweetpotato starch samples with wide range of quality parameters should be considered to improve model calibrations in future work. Further works are required to improve the accuracy of other sweetpotato starch quality indexes.

Sweetpotato starch can be used as a good raw material to produce noodles that a low-carb alternative to traditional pasta. Three parameters including CL, CR and SWD were used to indicate the quality of sweetpotato noodles and nondestructively evaluated by NIR technique, with good performance observed in CR prediction ($R_P^2 = 0.887$, SEP = 0.528), and weak behaviors in other two parameters (Lu et al., 2006a). By contrast, a better result was achieved in quantifying TVC presented on the surface of semi-dried purple-flesh sweetpotato noodles with almost the same range of spectral information. Based on the smell, color and TVC, the semi-dried noodles were classified into three categories of fresh, semi-fresh and not fresh with 100% accuracy (Cao et al., 2016). By mixing two kinds of starch (corn and cassava) into sweetpotato starch to produce noodles, the sweetpotato noodles with non-adulterants and adulterants were 100% identified by NIR-based SVMDA model. The SNV + 1D spectra-based SVM calibration allowed for the rapid quantification of the two mixed starches in the starch mixture with R_P values larger than 0.92 (Chen et al., 2019). Noodles are one of the main products in the processing of sweetpotato starch, and there are a small number of reports on the application of NIR for quality evaluation of sweetpotato noodles. Future work should focus on the comprehensive evaluation of sweetpotato noodle quality via NIR analysis.

Sweetpotato flour is a versatile and nutritious ingredient that is derived from sweetpotato roots and produced by drying and then grinding sweetpotato roots into fine powders. This flour is gaining popularity as a gluten-free and nutrient-dense alternative to traditional wheat flour (Ayo-Omogie, 2021). Quality evaluation of sweetpotato flour is essential to ensure that the product meets specific standards and requirements. Using NIR spectroscopy for sweetpotato flour quality evaluation has been investigated in aspects of various indexes (listed in Appendix). The physicochemical and nutritional quality including moisture, protein, fiber, AIS, starch, amylose, glucose, cellulose, nitrogen, carbon, carbon and nitrogen isotopes, minerals, iodine blue value, and anthocyanin were evaluated by different research groups. Among, most of the quality parameters were well-predicted by the combination of NIR and linear multivariate calibration algorithms (i.e. MLR and PLS) ($R_P^2 > 0.80$), which are listed in Table 1. (Bu and Li, 2018; Diaz, Veal, & Chinn, 2014; Ding et al., 2015; Gouveia, Lebot, & Pinheiro de Carvalho, 2020; He et al., 2024). Among, the accuracy of protein prediction through NIR analysis reduced significantly for the freeze-dried sweetpotato flour processed by enzymes (R_P^2 changed from 0.99 to 0.69). Differently, the fiber was quantified in enzyme-treated sweetpotato flour ($R_P^2 = 0.65$–0.85), but not in unprocessed flour (Diaz et al., 2014). The $\delta^{13}C$ was very poorly measured and that meant the very weak linear relationship between NIR and $\delta^{13}C$ values (Gouveia et al., 2020). Besides, six feature NIR wavelengths (700, 772, 912, 1528, 1950, and 2400 nm) were selected to estimate the antioxidant activity of sweetpotato flour in terms of ABTS, DPPH, and Fe^{2+} chelating and performed very well ($R_P > 0.97$). Meanwhile, the powdered, pure, and adulterated flour samples were recognized with 100% accuracy based on the full 700–2500 nm data (Ding, Ni and Kokot, 2015). Mixed with different contents of water, purple sweetpotato flour were made into pastes and their rheological properties (*G*', *G*", *G**, *K*) were determined with good prediction accuracy by applying any of PLS, PCR, and BPANN algorithm to correlated with NIR data (921–1361 nm) ($R_P^2 > 0.96$), which could support the indirect but rapid prediction of 3D printability of sweetpotato pastes (Chen et al., 2021). In recent years, most studies focused on the quality evaluation of mixed sweetpotato flour based on NIR analysis. After oven-drying, both chemical and nutritional quality of mixed flours (sweetpotato, arrowroot, canna, cassava, taro) in terms of moisture, protein, and polysaccharides (starch, amylose, glucose, cellulose) concentrations were well-predicted by PLS models based on appropriate preprocessed spectral data within the 1000–2500 nm (4000–10,000 cm^{-1}) range ($0.83 \le R_P^2 \le 0.97$) (Kandpal et al., 2022; Masithoh et al., 2022; Masithoh, Amanah, Yoon, Joshi, & Cho, 2021; Masithoh, Lohumi, Yoon, Amanah, & Cho, 2020). The accuracies of predicting both moisture and protein were higher than that of other indexes, which is most likely due to the more NIR absorption of the two components in the spectral range. Using the same range spectral information, such mixed flours have also been classified with 100% accuracy generated using SNV spectra-based PCA analysis (Yuliyanda, Masithoh, Khuriyati, & Saputro, 2019), and 67% accuracy using SG2D + SNV

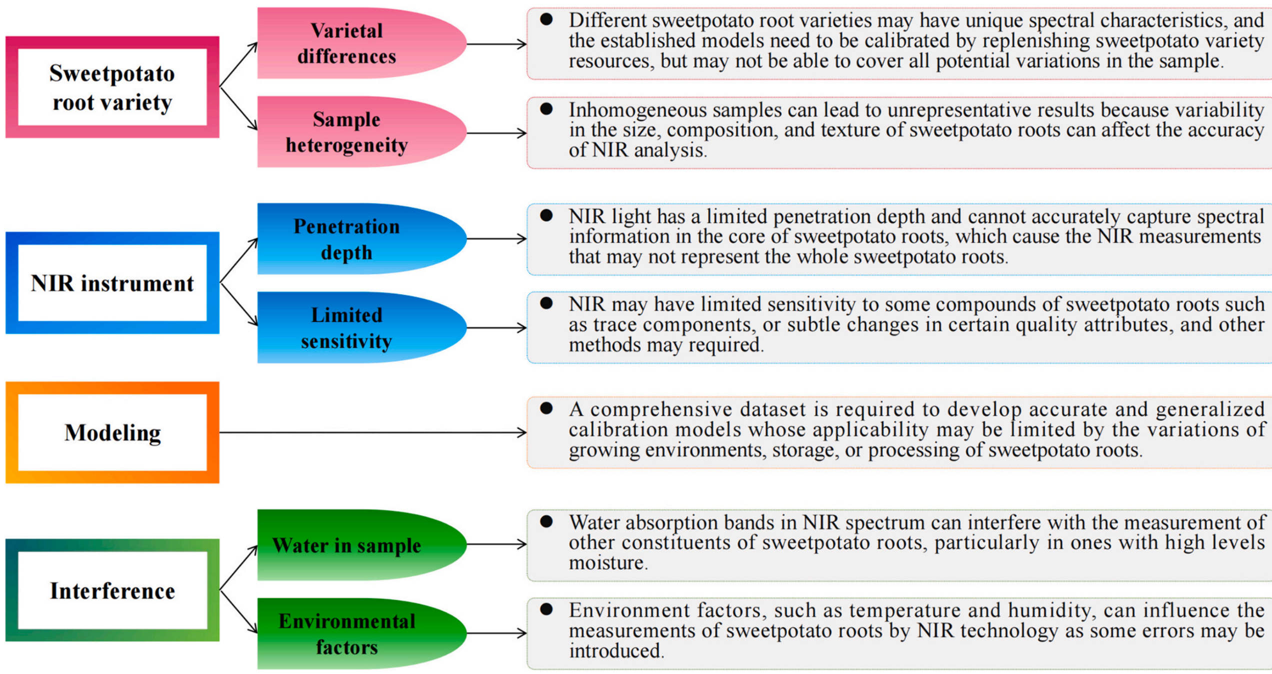

Fig. 6a. Challenges and limitations associated with NIR application for sweetpotato root quality evaluation.

spectra-based SIMCA analysis (Masithoh & Yuliyanda, 2019), indicating the different classification performance when employed different pre-processed spectra. In addition, considering the same range spectra, Masithoh, Amanah, and Cho (2020) used FT-NIR sensor to discriminate the root flours (canna, cassava, white sweetpotato) having similar color, aiming to minimize misclassification or avoid adulteration when using naked eyes. The results showed a 100% accuracy in discriminating all types of flours by PLSDA analysis. Both SG1D spectra-based PLSDA and feature wavelengths-based PLSDA also yielded perfect ability for discrimination ($R_P^2 > 0.99$).

It can be seen from all the studies, most of the research focused on NIR rapid detection of sweetpotato storage quality and product quality, which is driven by is driven by the need to enhance efficiency, reduce losses, meet consumer expectations, and optimize the economic and environmental sustainability of sweet potato production and distribution, highlighting the importance of addressing challenges in post-harvest handling, storage, and marketability. Sweetpotato roots are often stored for extended periods before consumption. Monitoring storage quality using NIR technology is crucial for preventing post-harvest losses, reducing spoilage, and ensuring the high quality attributes of sweetpotato roots during storage (Raju, 2021). NIR allows for non-destructive and rapid assessment of various quality parameters such as moisture, starch, and sugar contents, which is vital for preserving the texture, taste, and nutritional quality of sweetpotato roots, thus maintaining their market values. Rapid detection of storage quality employing NIR helps streamline the supply chain. By identifying potential issues at the early stage of storage, farmers and distributors can take corrective actions to minimize losses, improving work efficiency and supplying more consistent and high-quality sweetpotato roots (Prusky, 2011). The economic impact of post-harvest losses and reduced product quality is a significant driver for research in this area. Minimizing post-harvest losses and optimizing storage quality align with sustainability goals in agriculture (Stathers et al., 2020). Rapid detection of quality attributes using NIR contributes to cost savings, improved marketability, and increased economic returns for sweetpotato farmers. NIR studies focusing on product quality aim to meet market demands and consumer expectations, contributing to increased market competitiveness. On the other hand, consumer preferences for fresh, high-quality product promote the need for technologies that can rapidly assess and maintain the quality of sweetpotato roots (Ssali et al., 2021). In brief, NIR spectroscopy offers a rapid and non-destructive analytical method for assessing multiple quality parameters in sweetpotato products, contributing to improved process control and product quality. The NIR-based protocol developed from these studies can be used for screening large number of starch samples in food enterprises and sweetpotato breeding programs. In addition, importantly, to implement NIR spectroscopy for quality evaluation of sweetpotato roots and their products, a calibration model needs to be developed using representative samples with known properties. It's essential to regularly update and validate the calibration model to account for variations in raw materials and processing conditions.

5. Challenges and prospects

Although NIR spectroscopy is a powerful analytical tool, there are still several challenges and limitations in the application of sweetpotato root quality evaluation via NIR analysis, which are pointed out and shown in Fig. 6a. Several aspects in terms of sweetpotato variety, NIR instrument stability, calibration model reliability and high-efficiency, as well as minimal external interference affect the future scale application of NIR technology for quality assessment of sweetpotato roots. Different sweetpotato varieties may have varying physical properties (e.g. skin thickness, color, surface roughness) and chemical compositions (e.g. moisture, starch, polysaccharide, other constituents), and that can affect the accuracy of NIR measurements. Besides, sweetpotato roots heterogeneity in terms of size, shape, and internal compositions also potentially impact the NIR prediction if the developed calibration cannot cover all the variations within and between different varieties. As for NIR instrument itself, NIR light has limited penetration depth into the sample, leading to the insufficient information captured from the inner layers of thick or dense sweetpotato roots, and thus influencing the inaccurate NIR measurements of internal compositions. For some some trace components or subtle varies, the NIR sensitivity may be limited. The modeling process with calibration and validation requires a comprehensive dataset, and the model applicability may be affected by the variations of growing environments, storage, or processing of sweetpotato roots. NIR spectra can be mainly influenced by moisture levels and various environmental factors. NIR is sensitive to moisture

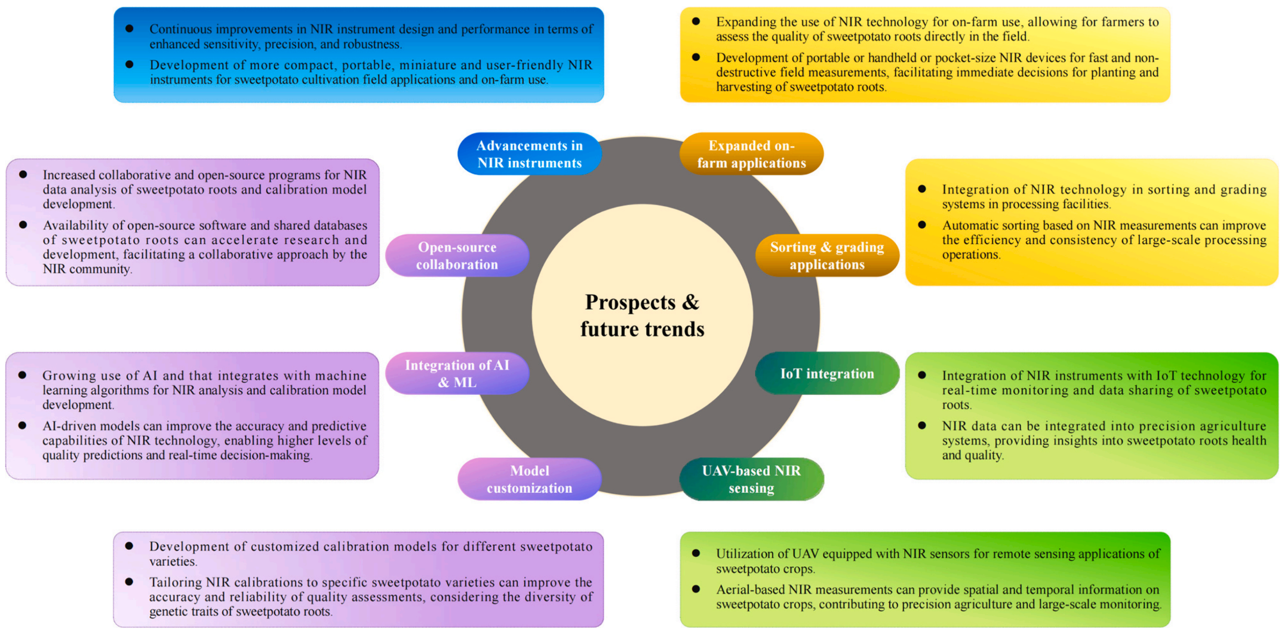

Fig. 6b. Prospects and trends associated with NIR application for sweetpotato root quality evaluation.

content, and variations in the water content of sweetpotato roots can affect the accuracy of NIR determinations. Moisture concentration can vary not only among different sweetpotato varieties but also within the same variety with the changes of environmental conditions and storage. The temperature and humidity are especially important environmental factors influencing the NIR accuracy as some errors may be introduced. To address these limitations, it's essential to develop robust calibration models that encompass a wide range of sweetpotato varieties by considering sample variability, genetic diversity, moisture content, and environmental conditions. In addition, combining NIR technology with complementary analytical techniques may enhance the overall accuracy and reliability of sweetpotato root quality assessment.

Despite these challenges and limitations, NIR spectroscopy remains a valuable and widely used technology for sweetpotato root quality evaluation when appropriately applied and carefully managed. Continuous advancements in instrumentation, calibration methods, and data analysis techniques contribute to addressing and mitigating these challenges, making NIR an increasingly reliable and accessible technology for agricultural quality assessment.

The prospects and trends of NIR technology for sweetpotato root quality evaluation in terms of hardware, software, application and integration with other technologies are proposed and shown in Fig. 6b, which indicate a promising future with ongoing advancements and increasing adoption of NIR analysis. The NIR instrument improvements including sensitivity, precision, and robustness will promote the NIR performance. More compact, portable, miniature and user-friendly NIR instruments will be designed and developed for field applications and on-farm use during sweetpotato cultivation. The software advancements mainly involving open-source programs, database sharing, integration of AI and ML, as well as model customization will facilitate collaborations between different disciplines and allow for the higher levels of NIR predictions and real-time decision-making. During application, portable or handheld or pocket-size NIR devices can be developed for on-farm use, allowing for farmers to assess the sweetpotato roots quality and facilitating immediate decisions for planting and harvesting of sweetpotato roots. Automatic sorting and grading based on NIR measurements can be used in processing, and that will improve the efficiency and consistency of large-scale operations. NIR sensors can also be integrated with IoT technology for real-time monitoring and data sharing of sweetpotato roots, or embedded into UAV for remote sensing applications of sweetpotato crops.

Through ongoing technological advancements, increased accessibility, integration with other emerging technologies, and a growing emphasis on sustainability and precision agriculture, the development of NIR applications and collaborative efforts within the scientific community will further enhance its capabilities for supporting efficient and quality-focused sweetpotato cultivation and processing.

CRediT authorship contribution statement

Yuling Wang: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Longzhu Xing:** Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing. **Hong-Ju He:** Writing – review & editing, Writing – original draft, Project administration, Funding acquisition, Conceptualization. **Jie Zhang:** Writing – review & editing. **Kit Wayne Chew:** Methodology, Investigation. **Xingqi Ou:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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