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REVIEW

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Emerging rapid and non-destructive techniques for quality and safety evaluation of cacao: recent advances, challenges, and future trends

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Abstract

Cacao is one of the world's most highly sought-after agricultural commodities for its great nutritional and economic importance. The cacao's quality is an essential parameter to consider during postharvest processes to satisfy consumers' preferences and commercial acceptability. However, the quality and safety evaluation of cacao is mostly monitored using human inspection, which is arduous because it requires more effort and offers inaccurate results, as human judgment is subjective. Furthermore, the conventional method for quality evaluation, such as cut-test and chromatographic analysis, is destructive in nature, resulting in the disposal of samples after the measurement is carried out. To overcome the drawbacks and challenges offered by conventional methods, the rapid and non-destructive technique was introduced. This study focuses on the application of emerging rapid and non-destructive approaches that have been used to monitor the quality and safety of cacao, notably during the harvesting, grading/sorting, fermentation, and postharvest processes. It includes imaging-based computer vision, spectroscopic-based techniques, hyperspectral imaging techniques, and other non-destructive techniques. Non-destructive techniques can evaluate the different internal and external quality parameters of cacao, such as maturity index, fermentation index, moisture content, total fat content, pH, total phenolic compounds, and others. This review also highlighted the advantages, drawbacks, and future perspectives of rapid and non-invasive techniques for evaluating the quality of cacao beans. This current work has proven the effectiveness of rapid and non-invasive in replacing the conventional methods for evaluating the quality of cacao.

Keywords Cacao, Quality Evaluation, Non-destructive Techniques, Noninvasive, Spectroscopic-based, Imaging-based, Hyperspectral imaging

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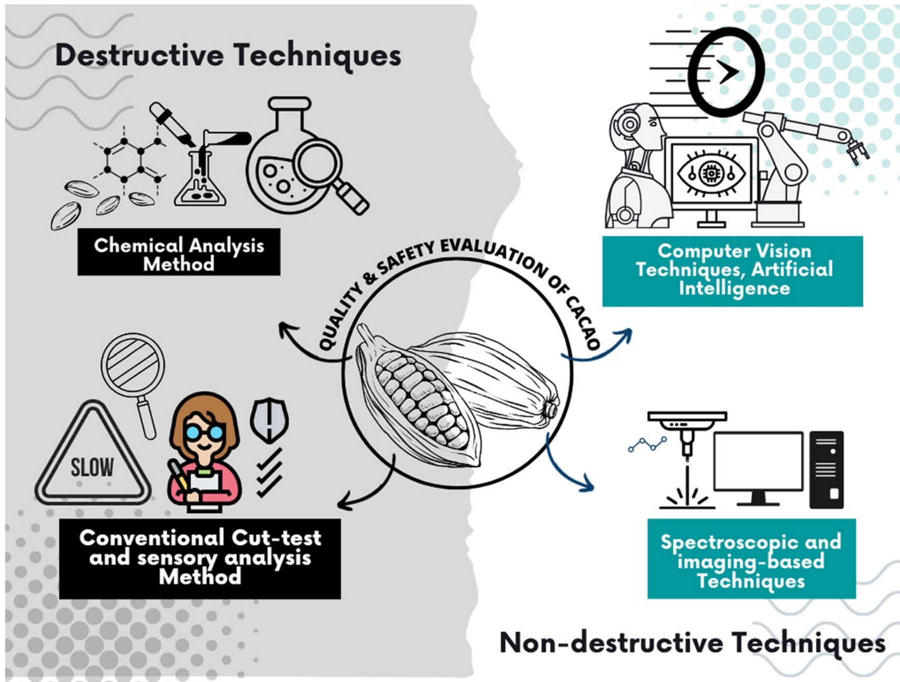
Graphical Abstract



Introduction

Cacao (*Theobroma cacao L.*) is a tree that bears cacao pods from which the cocoa beans (Fig. 1) are derived (Patel & Watson 2018). Cacao is popular worldwide as it is the raw material for making cocoa powder, chocolate, and confectionery products. Cacao and its products are valued for their aroma, color, and high health-beneficial properties and are considered highly valued commodities worldwide. It also offers significant economic importance in many developing countries in Asia, Africa, and Latin America (Jentzsch et al. 2016). Based on the projection of the International Cocoa Organization (2020), approximately 4.70 million tons of cacao beans were produced in 2019–2020 worldwide. The Philippines ranked fourth in the total production of cacao beans in the Asia Pacific region with 8,489 tons, while Indonesia is cited as the major producer of cacao beans worldwide with 783,978 tons (Statista 2020).

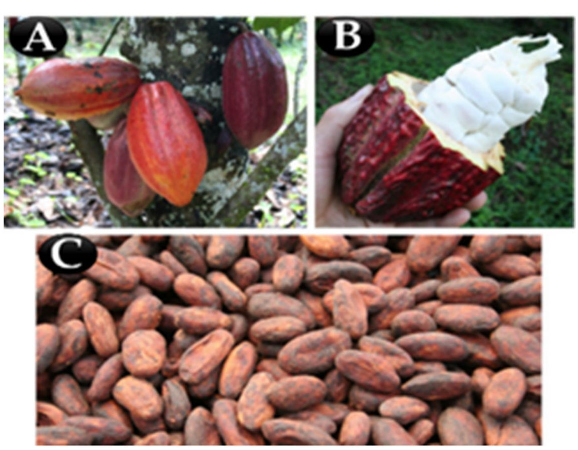


Fig. 1 The Cacao pods (**A**), Fresh Cacao beans in the pod (**B**), and Dried Cacao Beans (**C**). Source: Kim et al. (2011)

The continuous growth of the cocoa industry has gained significant interest for food processors to evaluate the quality of cacao during production, harvest, and post-harvest stages. These operations include classification based on the fermentation index, maturity index, morphology, and according to the chemical composition of the bean. The desire for quality evaluation of cacao pods and cocoa beans is governed by the demand to produce good quality of cacao products for the consumers and prevent losses for the cacao growers. The methodologies used to categorize beans in the majority of cacao industries worldwide involve 26-h-long chemical, physical, and sensory evaluations (Aculey et al. 2010). Additionally, 100 grains per ton samples are frequently used in this categorization to assess the load's quality. The analysis requires tasters, professional staff, specific tools, and sample destruction (Lecumberri et al. 2007; Saltini et al. 2013).

Among these, the cut-test is the most popular technique to assess safety, evaluate the fermentation index, and monitor the quality of cacao beans. Cut-tests are carried out at various stages of fermentation. The advantage of the cut-test is that it does not need specialized tools or high-level expertise. The cut-test is important for checking the quality of commercial beans. It also enables quick monitoring of the fermentation's progress since the color of the cocoa bean changes throughout fermentation from gray to violet to brown. However, the cut-test approach requires manual counting and is not a precise engineering method (Nguyen et al. 2022). Another advanced destructive technique is chromatographic analysis, a new and more sensitive method that can detect metabolites and contaminants in trace quantities (Quelal-Vásconez et al. 2020). Although the technique is reliable, however; it is destructive in nature, and sample preparation is lengthy. A sensory test is another conventional method used to determine the quality of cacao, particularly the flavor, texture, aroma, color, and appearance. Aside from being destructive, the approach is subjective, as different panels have different perspectives. For instance, Ilangantileke et al. (1991) demonstrated the sensory and cut-test procedure, and the results revealed inconsistencies and deficiencies in evaluating the cacao bean quality. Therefore, innovative non-invasive techniques are exploited to rapidly, objectively, and accurately monitor the quality of cacao beans without destructing the system.

In recent years, rapid and non-invasive techniques have been used to monitor and evaluate the quality of potatoes and sweet potatoes (Sanchez et al. 2019), evaluate the internal and external quality of watermelon (Mohd Ali et al. 2017a), evaluate the quality of mango (Ong et al. 2020), determine the quality of pineapples (Mohd Ali et al. 2020a), fruit, vegetables, and mushrooms (Wieme et al. 2022), spices (Modupalli et al. 2021), peanut (Rabanera et al. 2021), pork and beef (Sanchez et al. 2022a), detection of food quality and safety (Chen et al. 2013; Gu et al. 2021; Su et al. 2017). These non-invasive technologies have also been established to monitor and assess the different quality parameters of cacao during production to postharvest. Say, for example, the non-destructive capabilities of infrared spectroscopy and Fourier transform near-infrared (FT-NIR) spectroscopy have been employed to evaluate the internal quality of cacao beans (Barbin et al. 2018; Sunoj et al. 2016), to classify cacao bean using NIR-hyperspectral imaging (Cruz-Tirado et al. 2020), evaluate cacao pods maturity with the used laser-induced backscattering imaging (LLBI) (Lockman et al. 2019), predict the fermentation index (FI) of cacao bean using hyperspectral imaging (HSI) and artificial neural network (ANN) (Caporso et al. 2018; León-Roque et al. 2016).

Despite a substantial body of research on the evaluation of the quality and safety of cacao, a comprehensive overview of the quality and safety evaluation of cacao employing the emerging rapid and non-invasive methodologies has not yet been undertaken. Hence, this review paper aims to offer a comprehensive explanation of the numerous rapid and non-destructive techniques and their features, uses, limitations, and future developments in the quality and safety monitoring of cacao with a primary focus on the production and post-harvest processes such as the quality evaluation based on maturity index, fermentation index, and other postharvest activities such as grading/sorting, drying, and storage.

Quality evaluation of cacao

Quality and safety evaluation plays a crucial part in the food industry as customers get increasingly pickier and wiser when selecting their food products. Given that they are healthier, safer, and more dependable, most customers prefer high-quality, reliable foods (Sanchez et al. 2022a, 2022b). According to Sanchez et al. (2019), the quality evaluation of agricultural commodities is based on their various properties, such as internal and external properties. For instance, consumers' acceptability and commercial value of agricultural commodities greatly rely on their quality, particularly in cacao. For cacao, its' price is mainly controlled by its quality, which is governed by various factors, including appropriate farming practices, harvest point, and fermentation level (Sánchez 2020). It is necessary to identify and evaluate the quality of fruits and other agricultural commodities, particularly during postharvest handling, because the consumers' demand for high-quality fruit is growing (Ong et al. 2020).

The quality attributes of cacao beans are greatly influenced by the type of weather conditions, soil, ripeness level, and postharvest handling processes such as fermentation, drying, and storage (Bastide 2016; Cardona et al. 2016). Cacao beans fermentation is essential because cocoa flavor and taste are formed during this period. To produce more uniform and high-quality cocoa beans and to achieve greater homogeneity in the production of aroma and flavor precursors during cocoa processing—qualities that the chocolate industry highly values—it is imperative to understand the effects of these variables on the characteristics of cacao beans during drying and fermentation (Rojas et al. 2020). Characterization, classification, identification, authentication, and discrimination of cocoa beans from various types, as well as the location of origin, have all been researched for cacao bean quality evaluation (Teye et al. 2020). Among the most critical parameters to consider in evaluating a good quality cacao bean during the postharvest stage includes the maturity index, fermentation index, sugar level, and defects.

Non-destructive techniques

Generally, the cocoa industry is highly dynamic and has a complex supply chain. It is anticipated to gain from the growing interest in non-destructive techniques and chemical-free analytical procedures as a sophisticated, rapid, minimal sample preparation and straightforward approach. The non-destructive technique involves the measurement of its chemical composition, structural and physical characteristics, and other parameters related to its quality without destruction of its functionality as well as system characteristics (Mohd Ali et al. 2017a). As reported by El-Mesery et al. (2019a, 2019b), non-destructive techniques as a method of evaluation and measurement have gained high regard in the different fields of science, particularly in the food industry. For the quality evaluation of cacao, the most employed techniques were imaging based on computer vision, hyperspectral imaging, and spectroscopy. These techniques have their own unique feature in data acquisition and in monitoring the quality of cacao during the processes. Hyperspectral imaging is suitable for analyzing a wide spectrum of light, whereas spectroscopic-based techniques are more appropriate in single-spectrum acquisition. Imaging based on computer vision employs an algorithm and artificial vision to enable the collection, analysis, and comprehension of pictures to provide numerical and symbolic information for simple interpretation. With their unique features, they also have their own limitations which can also be filled by another approach. For instance, several properties, such as size, texture, shape, color, and defects, may be evaluated and assessed automatically utilizing a computer vision system. However, some defects are difficult to notice because their texture and color are indistinguishable from the skin (Bhargava & Bansal 2021). This limitation in imaging based on computer vision can be addressed using another imaging method such as the hyperspectral imaging technique (Munera et al. 2021).

These techniques have shown great potential and would become necessary in the cocoa industry because of their numerous advantages. Therefore, using non-destructive techniques to monitor the quality of cocoa beans during production to post-harvest is a goal of the researchers and the cocoa industry. The evaluation of cacao bean quality during post-harvest is a critical factor because, during this stage, the cocoa flavor and aroma are formed, which is also a great indicator of its quality. Various bacteria and enzymes work on the phenolic compounds, proteins, lipids, and carbohydrates in cocoa beans during fermentation, influencing the quality of chocolate and products containing cocoa (Caporaso et al. 2018). The use of rapid, non-destructive methods to evaluate cocoa bean quality is expanding right now. The quality of cocoa pods and beans was assessed using non-destructive technologies such as imaging, spectroscopic, computer vision, and other non-destructive methods. Applications of non-destructive technology for cacao quality assessment are shown in Table 1.

Hyperspectral imaging techniques

Hyperspectral imaging (HSI), a new non-destructive instrument used for quality evaluation and control in the area of food science and technology, has the ability to define a sample's fundamental chemical components (Calvini et al. 2016; Li et al. 2017). The basic idea behind this technology is to analyze a wide spectrum of light rather than only assigning primary colors like red, green, and blue to each pixel. The light striking each pixel is divided into various spectral bands to provide additional information about what is captured (Schneider & Feussner 2017). As illustrated in Fig. 2, HSI exhibited promising performance, particularly as a non-destructive technique in the cocoa industry. Individual grain or bean samples may be analyzed swiftly, non-destructively, and without contact, and samples can be scanned at high throughput while showing geographical dispersion (Caporaso et al. 2018). HSI can operate at different electromagnetic measurements, such as visible (VIS), near-infrared (NIR), middle infrared (MIR), and Raman spectroscopy (Amigo 2019). Among these, near-infrared hyperspectral imaging (NIR-HSI) is the most exploited non-destructive technique for the quality and safety evaluation of cacao. It utilizes the spectral range of 780–2500 nm and has grown in popularity for quickly gathering data to enable the measurement, identification, or distinction of several bean attributes.

In the cocoa industry, classification refers to the process of categorizing samples depending on several factors such as variety, origin, fermentation level, etc. It is crucial to recognize hybrid samples since they require different treatments during the manufacturing process and have distinct commercial value. For instance, Cruz-Tirado et al. (2020) used near-infrared hyperspectral imaging (NIR-HSI) as a rapid and non-invasive procedure to identify and classify cacao bean hybrids. Five cacao beans were discriminated against using the Partial Least Squares discriminant analysis (PLS-DA) and Support Vector Machines (SVM). A reliable result for the classification of beans for two-class models with 70–100% classification rate and 100% classification rate for five-class models. The study has exhibited reliable success in

Table 1 Recent applications of rapid and non-destructive methods for in the quality and safety evaluation of Cacao

Application	Quality Parameters	Data Analysis	Results	References
NIR-Hyperspectral imaging	Classification	PLS-DA, SVM	Prediction error: 3.8–23.1% (SVM) 4.4–34.4% (PLS-DA)	Cruz-Tirado et al. (2020)
Hyperspectral imaging	Classification, FI	PLSR	95% accuracy	Bayona et al. (2018)
Hyperspectral imaging	FI, TP, AA	PLSR	$R^2=0.5$ (RMSEP = 0.27, RPD = 1.40) for FI $R^2=0.7$ (RMSEP = 34.1 mg ferulic acid g − 1, RPD = 1.77) for TP $R^2=0.74$ (60.0 mmol Trolog kg − 1, RPD = 1.91) for AA	Caporaso et al. (2018)
Hyperspectral imaging	FI	SVM	63.3%-90% accuracy	Sanchez et al. (2020)
Hyperspectral imaging	Classification	PCA, SVM, LDN, KNN	81.28%-89.10% accuracy	Saeidan et al. (2021)
Hyperspectral chemical imaging	Total fat content	PLSR	$R^2=0.84$, external prediction error of 2.4% for single shelled; $R^2=0.52$, predection error 4.0% for in-shell beans	Caporaso et al. (2021)
Laser-induced backscattering imaging	Firmness and maturity	PLSR	$R^2=0.755$ for 658 nm & $R^2=0.800$ for 705 nm for chroma; 90%-95% classification accuracy	Lockman et al. (2019)
FT-NIR spectroscopy	Fermentation index, pH, and total polyphenol content	ANOVA, LSD	$R^2 \geq 0.80$ (FI and polyphenol) $R^2 < 0.80$ (pH)	Sunoj et al. (2016)
FT-NIR spectroscopy	Total fat content	Multivariate Regression, Si-PLS, SVMR, Si-SVMR	RMSEP = 0.015 and $R_{pre}=0.9708$	Teye and Huang (2015)
FT-NIR spectroscopy	Classification	LDA, SVM	100% classification accuracy	Teye et al. (2016)
FT-NIR spectroscopy	Total fungi count	PLS, Si-PLS,Si-GAPLS, ACO-PLS, CARS-PLS	$0.951 \leq R_{pre} \leq 0.975$ & $3.15 \leq RPD \leq 4.32$	Kutsanedzie et al. (2018)
NIR Spectroscopy	Classification, Internal quality	ANOVA, PLSR	RMSE up to 0.99, $R_c{}^2$ up to 0.99 RMSE up to 1.19 $R_p{}^2$ up to 0.97 for whole and ground	Barbin et al. (2018)
NIR Spectroscopy	Internal quality	PCR, PLSR, MSC, DT, SNV, OSC	$R^2=0.86$ RPD = 3.16 (Fat Content), $R^2=0.92$ RPD = 3.43 (Moisture Content)	Hayati et al. (2020)
NIR Spectroscopy	Internal quality	PLSR	$R^2=0.67$–0.89, relative error < 10.2%	Hashimoto et al. (2018)
NIR Spectroscopy	Internal quality	MPLSR, SNV, DT, PLS	$R^2=0.77$ (theobromine, $R^2=0.74$ (total sugar), $R^2=0.66$ (total phenols), $R^2=0.88$ (derivatives of epicatechin), $R^2=0.7$ (fat), R^2=0.64 (protein, $R^2=0.82$ (husk content)	Hernández-Hernández et al. (2022)
NIR Spectroscopy	Fermentation Level	PCA	$R^2=0.975$, $R_{pre}=0.935$	Hue et al. (2014)
NIR Spectroscopy	Classification	CAFS, NBC, ECFS, MCFS	Average accuracy: 99.63% (NBC), 94.92% (ECFS), & 99.63% (MCFS)	Castro et al. (2022)
Artificial Neural Network	Fermentation index	Coefficient of determination, Bland–Altman plor, Passing-Bablok Regression analysis	No accuracy specified	Leon-Roque et al. (2016)

Table 1 (continued)

Application	Quality Parameters	Data Analysis	Results	References
Machine Vision and Multiclass SVM Classifier	Classification based on fermentation degree	SVM	100% accuracy	Yro et al. (2018)
Digital Imaging	Classification based on morphology	MELS-SVM	99.705% accuracy	Lawi and Adhitya (2018)
Multiparametric fluorescence sensor	Anthocyanin, flavanol, chlorophyll and nitrogen balance	PCA, CA	Accuracy was not specified	Tee et al. (2018)
Electronic nose Systems	Fermentation degree	bootstrap forest, decision tree, boosted tree, ANN, naïve Bayes, k-nearest neighbors	Misclassification rate: 9.4% (bootstrap forest), 12.8% (ANN), 13.6% (boosted tree)	Tan et al. (2019)
Electronic Nose	Grading	ANOVA	RMSE ~ 1% (KDM), RMSE = 2.9%-9.3% (under different conditions)	Tan and Kerr (2019)
Electronic Nose	Grading	LDA, SVM, ANN	Overall accuracy: 99% (training data-set), 95% (external-validation dataset)	Hidayat et al. (2019)
Electronic Nose	Fermentation index	PCA	97.8% of the total variance	Flórez-Martinez et al. 2020
Electronic Nose	Classification	PCA	95% accuracy	Olunloyo et al. (2012)
NIR Spectroscopy & Electronic Tongue	Cocoa bean variety Classifications	Multivariate Analysis, PCA	83%-93% accuracy (single sensor) 100% accuracy (data fusion)	Teye et al. (2014a)

ANOVA Analysis of variance, *CA* Cluster analysis, *LSD* Least significant difference, *PCA* Principal component analysis, *PLSR* Partial Least Square Regression, *PLS-DA* Partial Least Squares discriminant analysis, *SVM* Support Vector Machines, *NIR* Near-infrared, *FT-NIR* Fourier transform near infrared, *Si-PLS* Synergy interval Partial Least Squares, *SVMR* Support Vector Machine Regression, *Si-SVMR* Support Vector Machine Regression, *RMSEP* Root-Mean-Square Error of Prediction, *MELS-SVM* Multiclass Ensemble Least-Squares Support Vector Machine, *PCR* Principal Component Regression, *Si-GAPLS* Synergy interval-genetic algorithm-PLS, *ACO-PLS* Ant colony optimization – PLS, *CARS-PLS* Competitive-adaptive reweighted sampling-PLS, *CAFS* Covering array feature selection, *NBC* Naïve Bayes classifier, *ECFS* Eigenvector centrality feature selection, *MCFS* Multi-cluster feature selection, *LDN* Linear Discriminant Analyses, *KNN* K Nearest Neighbours $\boldsymbol{R}^2$ coefficient of determination, *FI* Fermentation index, *TP* Total polyphenol, *AA* Antioxidant activity, *RMSEP* RMSE of cross-validation, *RPD* MSE of prediction, R_{pre} Correlation coefficient in prediction set, $\boldsymbol{R_c}^2$ Coefficient of calibration, $\boldsymbol{R_p}^2$ Coefficient of prediction, *MPLSR* Modified Partial Least Square Regression, *SNV* Standard Normal Variate, *DT* Detrending

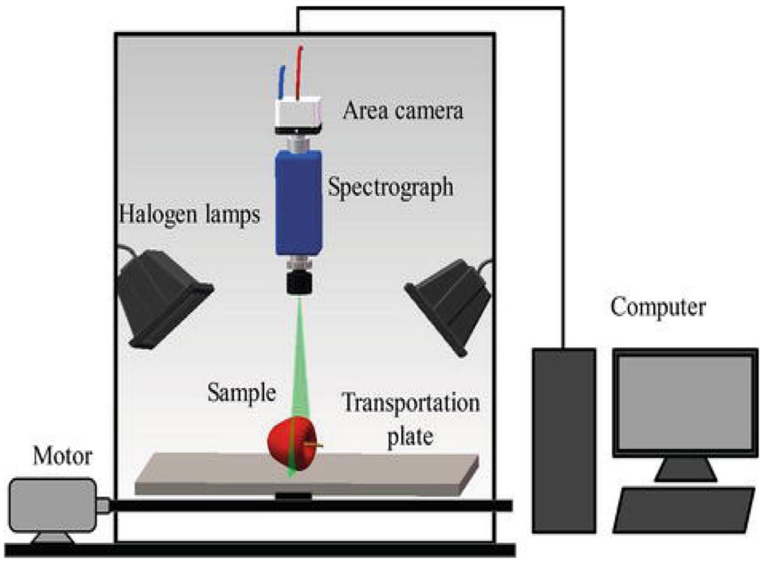


Fig. 2 A schematic illustration of the Hyperspectral Imaging system. Source: (Li. 2017)

terms of classifying hybrid cacao beans. Nevertheless, the feasibility of this approach, particularly in a more significant number of samples, still needs to be investigated. Sánchez et al. (2020) used hyperspectral image capture and processing techniques to describe 90 cocoa beans depending on fermentation level. Results revealed that the approach could differentiate the fermentation level of cocoa beans (slightly fermented, correctly fermented, and highly fermented). Similarly, Bayona et al. (2018) reported developing closed-range Hyperspectral images to distinguish two standard cocoa bean kinds at different phases of fermentation. The differences in anthocyanin concentrations between the two cultivars were more noticeable as fermentation progressed. As reported by Afoakwa et al. (2012), the anthocyanin content of cacao beans decreases as fermentation proceeds. Changes in the bean's biochemical processes greatly influenced its hyperspectral signatures, which offer better discrimination. As a result, success in terms of classifying different varieties of cacao beans during the different levels of fermentation stages using close-range hyperspectral images was observed.

Other relevant quality parameters of cacao beans are polyphenols, antioxidant activity, and the fermentation index. Polyphenols are antioxidant compound present in cocoa that offers numerous health benefits and are responsible for the bitter taste of raw coca beans (Li et al. 2012; Oracz et al. 2015). Polyphenols have gained popularity due to their physiological effects, which include antioxidant activity and the ability to prevent lipid oxidation. The fermentation index is an essential parameter that influences the formation of cocoa flavors. Hence, it is vital to investigate these parameters during the quality inspection of cacao beans. As a response, Caporaso et al. (2018) have investigated the quality of a single cacao bean with the use of HSI in the spectral range of 1000–2500 nm. Partial Least Squares regression (PLSR) was applied to build quantitative models extracted from HSI with a spectral range of 1000–2500 nm at 240 wavelength bands. Good prediction results were obtained on shelled cacao beans on a single-bean basis, where the best HSI calibrations allowed accurate visualization of the three relevant quality parameters of the cocoa bean. Similar to this, Caporaso et al. (2021) employed hyperspectral chemical imaging to determine the total amount of fat in each dried whole cocoa bean. In their study, 170 randomly selected cocoa beans were analyzed with the use of HSI. From the results of the PLSR model, lower prediction error (2.4% for shelled and 4% in-shell) and R^2 of 0.84 and 0.52 for shelled and in-shell were obtained, respectively. Figure 3 shows the visualization of fat across the beans, as shelled unground beans using single pixels. This analysis is an excellent example of how HSI can be employed to predict the fat content of cocoa beans in a non-contact manner, even from images of unshelled beans. This analysis has relevant practical advantages for the food industry in terms of quality control and acquiring a more consistent raw material.

Another imaging-based method that has gained wide attention in recent years is the laser-light backscattering imaging (LLBI) technology, simply known as backscattering imaging. LLBI is a new spectral imaging tool that is notable for its ability to monitor samples without touching them and for its minimal instrumentation cost while

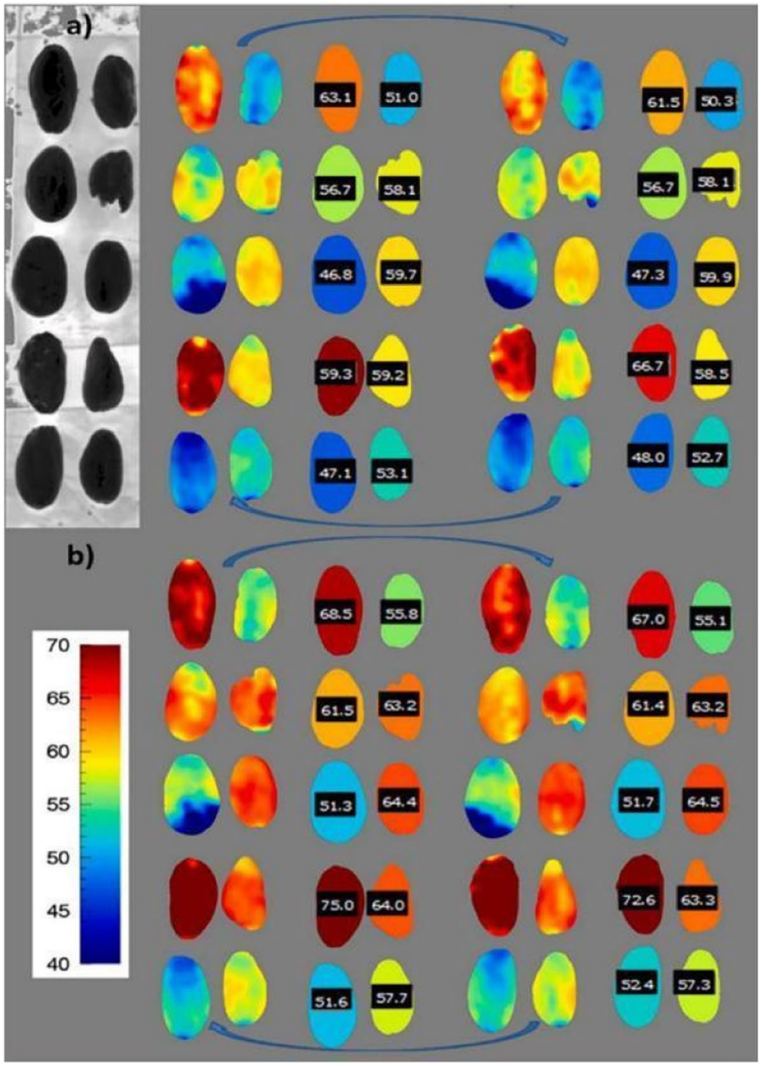


Fig. 3 Calibration models were used to visualize total fat content in unroasted whole cocoa beans (unshelled) at a single pixel level, predicted on (**a**) "as is" or (**b**) dry matter basis. The beans are presented in both orientations, and the numbers represent the expected average value for each bean (batch from Ivory Coast). Source: Caporaso et al. (2021)

maintaining excellent accuracy (Mollazade et al. 2018). The idea behind backscattering imaging is to capture the light that is dispersed as a result of the interaction between the laser light and the food material being examined (Sanchez et al. 2020). Lockman et al. (2019) used this method to assess the firmness and color of cocoa pods at various stages of maturity. An unripe cocoa pod's skin is often green or reddish purple, and when it is mature, it turns yellowish (Montamayor et al. 2013). As a result, it may be manually categorized using color identification. However, due to erratic weather conditions, the cacao pods do not change color when it is ripe. Hence, the backscattering imaging under 658–705 nm wavelength was explored, and the quality parameters, such as firmness and color values, were examined. The study's findings demonstrated a strong correlation between the reference parameters and backscattering parameters, with an R2 of more than 0.90 and classification values of more than 90% using PLSR analysis. Thus, the backscattering imaging method can be a reliable approach for determining cacao firmness and maturity levels (unripe, ripe, and over-ripe).

Spectroscopic-based techniques

Spectroscopy-based techniques are methods that utilize radiated energy to evaluate the characteristics and properties of materials or samples (Dahman 2017). These techniques are known for their comprehensive applications in different fields and disciplines, predominantly in non-destructive food and safety assessment (Mohd Ali et al. 2020). The use of well-established non-destructive analytical methods based on spectroscopy enables the precise, fast, and direct evaluation of a variety of properties without the need for sample pre-treatment (Sun 2009). Under this technique is the Fourier transform near-infrared (FT-NIR) spectroscopy, a technique for obtaining the infrared spectrum of absorption, emission, and photoconductivity of solids, liquids, and gases (Sindhu et al. 2015). Since it involves no sample preparation and may be conducted in less than a minute, FT-NIR spectroscopy can be a valuable method for estimating commodity quality rapidly. In previous years, FT-NIR spectroscopy has demonstrated reliable success in terms of evaluating and monitoring the different quality parameters of beans and grains such as green coffee beans (Taradolsirithitikul et al. 2016), roasted coffee beans (Craig et al. 2015), soybean (Amanah et al. 2020, 2022; Ferreira et al. 2013), mung bean (Qian et al. 2022), rice (Peijin et al. 2021), wheat (Amir et al. 2013), and other agricultural products (Tao et al. 2018). A feasibility study on the application of FT-NIR spectroscopy to quantify and classify cocoa beans was carried out by Teye et al. (2014a). Good results were obtained, and it concluded that FT-NIR spectroscopy, together with the appropriate multivariate algorithm, can be applied as a reliable tool to quantify and classify cocoa beans based on different classifications.

Sunoj et al. (2016) investigated the use of non-destructive FT-NIR spectroscopy to assess key quality indicators such as fermentation index, pH, and total polyphenol content in whole cocoa beans. This study established calibration models such as R^2 and root mean square error for cross-validation (RMSECV) based on the FT-NIR spectral characteristics. Other chemometric parameters namely: vector normalization, multiplicative scatter correction (MSC), and first derivative (FD) were also developed to assess the capability of the technique used. Basic descriptive statistics, analysis of variance (ANOVA), and least significant difference (LSD) for the post-hoc analysis were likewise employed. Results revealed that the FT-NIR spectroscopy has a strong potential in predicting the quality attributes of cocoa beans with optimum fermentation index of ($R^2=0.88$, RMSECV$=0.06$, Residual Prediction Deviation (RD)$=2.74$) and total polyphenols ($R^2=0.84$, RMSECV$=0.93$, RD$=2.53$) compared to the pH ($R^2=0.76$, RMSECV$=0.26$, RD$=2.05$) of cacao beans. Increasing the amount of samples also improves the models and projections. When compared to the standard cut-test and chemometric approaches (with approximately 28 h), this method is proven to be faster since it can predict the mentioned quality criteria in an instant (less than 1 min). The use of FT-NIR calibration methods could be a reliable tool in predicting quality attributes in a single scan over cocoa beans, with findings available in a minute or less.

The total fat content of cacao bean is one of the major quality attributes that a chocolate manufacturer and producer consider the most as it is a major essential component of chocolate formation. Thus, it is also vital to evaluate the total fat content of a single cacao bean during the process. A rapid and non-invasive approach is a necessary method, especially nowadays, the demand for high-quality cocoa products is rapidly growing. Fortunately, Teye and Huang (2015) reported the establishment of FT-NIR spectroscopy based on a unique systematic study on effective spectral variables selection multivariate regression to measure the amount of fat in cacao beans. The total fat content of cocoa beans could be rapidly and non-destructively predicted using FT-NIR spectroscopy. Likewise, Teye et al. (2016) used a similar approach for the non-destructive identification of cocoa beans with different cultivars. In their study, five different cultivars were scanned in the near-infrared range of 10,000–4000. To create discrimination models based on principal component analysis (PCA), support vector machine (SVM) algorithms and linear discriminant analysis (LDA) were both executed. Cross-validation was used to optimize the models for stability. The SVM model achieved a 100% identification rate in both the training and prediction sets.

Another example of a spectroscopic-based technique better suited for quantitative analysis of complicated mixtures is Near-infrared spectroscopy (NIRS), a spectroscopy that operates in the wavelength range of 800–2500 nm (Su et al. 2015). This approach concerns the absorption, emission, reflection, and diffusion of light to the samples (Ozaki et al. 2017). Due to its numerous benefits over alternative analytical techniques, this approach has been used widely in agriculture, food engineering, and other fields. Barbin et al. (2018) developed the use of this technology as an analytical tool to categorize various cocoa bean kinds and predict the chemical and physical characteristics of cocoa for both whole and ground samples. The differences in the chemical composition in cocoa varieties were compared with ANOVA and PLS Regression models for predicting chemical components and color features. The use of near-infrared spectroscopy could aid in creating a reasonably easy and automated approach for sorting cocoa beans into distinct types and predicting the chemical composition of fermented and dried cocoa beans and the color characteristics of ground cocoa samples. Similar methods were used by Hashimoto et al. (2018) to assess the quality and safety of coca beans, including the estimation of their moisture content, acidity, pH, shell content, fat content, protein content, total phenolic content, caffeine content, and theobromine concentration. All of these parameters were correctly predicted with relative errors of less than 10.2% and a sufficient coefficient of determination ranging from 0.67 to 0.89.

A considerable rise was noticed depending on the fermentation duration, making the ammonia nitrogen (NH3) concentration of cocoa beans a suitable fermentation marker. Hue et al. (2014) determined the fermentation stage of cocoa samples easily by studying them using NIR spectroscopy. With a standard error of prediction of 20 ppm, the calibration model created was capable of precisely determining the content of cocoa beans using NIR spectroscopy. The authors have finally come to the conclusion that NIR spectroscopy can be employed as a quick, precise, and non-intrusive method for tracking the fermentation progress of cocoa beans. In 2020, Hayati et al. (2020) also used NIR spectroscopy to rapidly and simultaneously determine several internal quality characteristics of cocoa beans, such as the fat and moisture content. The greatest correlation of determination (R^2) and residual predictive deviation (RPD) index for predicting fat content were 0.86 and 3.16, respectively, and 0.92 and 3.43, respectively, for predicting moisture content. In order to swiftly and concurrently anticipate the internal quality attributes of intact cocoa beans, NIRS may be used in conjunction with an appropriate spectrum correction technique.

Imaging-based techniques

Imaging techniques based on computer vision use an algorithm and artificial vision that will allow the acquisition, analysis, and understanding of images to produce numerical and symbolic information for easy interpretation (Szeliski 2011). This technology, rather than relying on human sight, employs a camera and computer to detect, track, and measure targets for subsequent image processing (Tan et al. 2019). Because of the multiple benefits acquired, such as effectiveness and quality, computer vision techniques have been utilized to automate activities in the agriculture industry. This new technology has been utilized to examine the quality of fruits and vegetables in a quick and non-destructive manner (Bhargava & Bansal 2021; Zhang et al. 2014; Mahendran et al. 2012; Chopde et al. 2017; Tripathi et al. 2020; Raponi et al. 2017), grains (Patrício, D. I., & Rieder, R. 2018; Jayas et al. 2012; Lee et al. 2011), beans (Mite-Baidal et al. 2019; García et al. 2019), and various food products (Sun 2009; Mogol et al. 2014, Brosnan et al. 2004; Tretola et al. 2017; Ma et al. 2016; Aguilera et al. 2007).

For the quality inspection of cacao, León-Roque et al. (2016) predicted the fermentation index of cacao beans using Artificial Neural Network (ANNs) based on color measurements. Two raw white fine cocoa beans of criollo types from Piura (M1) and Cajamarca-Per (M2), as well as one native criollo variety (M3) from Tumbes-Peru, were used in their investigation. The authors were able to discriminate the fermentation index of three cocoa bean kinds that were comparable to the experimental results obtained in a validation test sample that was randomly selected. The suggested ANNs model could be used as a non-destructive, low-cost, in-situ approach to efficiently forecast FI in fermented cocoa beans using mobile device apps. Yro et al. (2018) reported the potential of Machine Vision and Multiclass Support Vector Machine (SVM) Classifier to identify the cacao beans based on fermentation degree. In their study, the image was captured, and the beans were separately recognized from the background. Results showed that a machine vision system combined with SVM could distinguish cacao beans depending on their level of fermentation with a 100% discrimination rate for both training and prediction sets. Parra et al. (2018) employed computer vision techniques to estimate the cacao beans fermentation index, and the results exhibited 75% classification accuracy based on information of color in RGB format.

Likewise, Lawi and Adhitya (2018) investigated the quality of cocoa beans in terms of morphology through digital images with the use of Multiclass Ensemble Least-Squares Support Vector Machine. Under controlled lighting conditions, cocoa beans were placed and scattered on bright white paper. The images acquired from the compact digital camera were then processed to extract the morphological parameters such as Area, Perimeter, Minor Axis Length, Major Axis Length, Aspect Ratio, Roundness, Circularity, Ferret Diameter. Based on their morphological features, the beans were classified into four classes' namely Normal beans (first class), Broken Beans (second class), Fractured Beans (third class), and Skin Damaged Beans (fourth class). Multiclass Ensemble Least-Squares Support Vector Machine (MELS-SVM) was used as a classification model. The result based on mentioned morphological parameters was found accurate, with a 99.705% accuracy level for all classes. Additionally, Jimenez et al. (2017) also established computer vision for classifying different varieties of cocoa beans and determining the percentage of their mixtures. By excluding samples with white beans and low fermentation levels, the result exhibited a promising result in terms of discrimination with a precision higher than 98%.

Other non-destructive techniques

Another noninvasive tool is the electronic nose system, a non-invasive technology that can identify basic or complex odors, is made up of a number of partial specificity electronic chemical sensors and a pattern recognition algorithm. The electronic nose is used to differentiate complicated volatiles by reproducing the structure and principles of the olfactory sense (Arakawa et al. 2022). This tool can provide objective results and has the potential to detect smells and odors that are not detectable by the human nose. The importance of the food industry has become more crucial with the development of society. With the introduction of this tool, a new alternative for non-destructive quality testing of agricultural and food commodities has emerged (Mohd Ali et al. 2020). It has been used as a tool for quality and safety inspection of broccoli (Ezhilan et al. 2019), strawberries (Liu et al. 2019), salmon (Jia et al.. 2020), pork (Da et al. 2021), meat and fish (Grassi et al. 2019), tea (Kaushal et al. 2022), foodstuff (Zhong et al. 2019; Sanaeifar et al. 2017; Sberveglieri et al. 2014; Falasconi et al. 2012), grains (Balasubramanian et al. 2007), and beans (Sberveglieri et al. 2012). Olunloyo et al. (2012) developed a prototype electronic nose to monitor and classify cocoa beans for the quality and safety evaluation of cacao. The results demonstrated a valid result as a 95% classification rate was obtained. Additionally, Tan et al. (2019) used six different machine-learning techniques to investigate the degree of fermentation in cocoa beans using an electronic nose system based on machine learning, including bootstrap forest, boosted tree, artificial neural network (ANN), decision tree, k-nearest neighbors, and naive Bayes. In their experiment, 75 kg of fresh cocoa beans were evenly dispersed in styrofoam coolers that were 60 cm by 30 cm by 30 cm and were kept in a controlled atmosphere. The misclassification rate obtained for the Bootstrap Forest algorithm, ANN, and boosted tree was 9.4%, 12.8%, and 13.6%, respectively. Though other methods failed to classify cocoa beans, the study still showed a promising result with a lower misclassification rate.

Furthermore, de Oliveira et al. (2018) investigated the extracted Caffeine (CF) and Theobromine (TB) from cacao with the use of protic ionic liquids (PILs) based on ultrasonic-assisted extraction (PIL-UAE). The ANOVA method was used to identify significant variables. ANOVA is made up of classified and cross-classified statistical results and was tested using a specified classification difference, as performed by Fisher's statistical test (F-test). The result showed that protic ionic liquid could be used instead of non-conventional solvents to extract alkaloids like theobromine and caffeine. This approach was also established by Hidayat et al. (2020) for the rapid determination of quality grades of superior java cocoa beans. Three multivariate statistical tools, namely SVM, LDA, and ANN, were used. The best result was obtained with the electronic nose ANN procedure, with 99% and 95% overall accuracy for the training and external validation datasets.

Teye et al. (2014a) also examined the possible use of sensor fusion for the speedy and precise categorization of five different types of fermented and dried cocoa beans using the electronic tongue (ET) and near-infrared spectroscopy (NIRS). Data acquisition was performed from each sensor, and the data fusion was done by normalization using Principal Component Analysis (PCA). A support vector machine was used in their study to create the classification model. To optimize the model, cross-validation was used to improve the model, and the number of principal components and classification rate. The result shows that data fusion (ET-NIRS) displayed promising results in terms of identification rate (100%) for both training and prediction tests.

In order to estimate the anthocyanin, flavanol, chlorophyll, and nitrogen balance in cacao pods of various cacao genotypes across varied pod development stages (1–5 months after pod emergence), Tee et al. (2018) investigated the use of a multiparametric fluorescence sensor. They also sought to identify the ideal cacao harvest time for high-quality beans under commercial practice using a Multiplex 3® sensor (Force-A, Orsay, France), cacao pods were examined at various phases of growth. A fluorimeter with six light-emitting diode sources in the UV-A (370 nm), blue (470 nm), green (516 nm), and red (635 nm) spectral areas comprised the sensor. Overall field fluorescence indices and post-harvest bean quality tests were correlated using principal component analysis (PCA) and cluster analysis (CA) for beans harvested four months (mature) and five months (ripe) following pod emergence. As cacao pods grew, flavanol levels increased, while chlorophyll and the NB index decreased as pods matured four months following emergence. Post-harvest bean quality tests found that pods collected four months after pod emergence met Malaysian Standard requirements, and bean quality is comparable to beans harvested five months following pod emergence.

In 2020, Tee et al. (2020) established the utilization of a fluorescence sensor for the determination of cacao pigments, flavonoids, and nitrogen content during its development. Five fluorescence-based portable sensor clones, DESA1, KKM25, KKM22, PBC221, and MCBC1, were used to determine the flavonol, anthocyanin, chlorophyll, and nitrogen balance was monitored monthly (1–5 months) later after flower fertilization. As an overall result of their study, it was found that the measurement of pigments and flavonoids present in cacao can give important non-destructive indications for cacao pod maturity across various cacao cultivars was found valid.

Benefits and drawbacks of non-destructive techniques for Cacao Bean

In recent years, rapid and non-invasive techniques emerged as popular tools for evaluating and analyzing food quality. Nondestructive technologies are a promising tool in the food industry as they exhibited success in evaluating and monitoring the different quality parameters of fruits, beans, and grains. For cacao beans, several nondestructive techniques were established for the purpose of quality inspection during production, harvest, and post-harvest processes. Unlike the conventional method, nondestructive techniques are at the forefront in terms of speed of analysis, ease of installation, and continuous monitoring of food quality across many samples (Mohd Ali et al. 2017c). This approach also provides accurate, efficient, and objective results. However, despite the numerous benefits acquired, these techniques are relatively high in terms of cost resulting to limitation of use, particularly in industrial and commercial settings. Furthermore, another notable disadvantage of this approach is that it requires higher technical knowledge or well-trained personnel to perform the hands-on operations, so growers or graders will choose not to use the system and instead use the traditional method (Sanchez et al. 2020). Various nondestructive techniques possessed unique advantages and constraints. In general, the benefits and drawbacks of nondestructive techniques are presented as encapsulated in Table 2.

Despite the prevalence of the described nondestructive techniques, hyperspectral imaging is the most often utilized method for evaluating cacao quality. This is because it is easier to set up than other nondestructive approaches. Additionally, HSI offers more accurate results as it correlates the spectral signature of cacao to its parameters at different stages or levels of fermentation, enabling users to predict its quality condition. Even so, this approach also has significant constraints, such as the series of consecutive overlapping bands obtained during the acquisition, which sometimes will lead to misclassification and incorrect findings.

Advancements, latest developments and future perspectives

Non-destructive food quality detection offers a distinct advantage over other instrumental and chemical analysis methods and a wide range of application possibilities and development potential. The following are some drawbacks of classical chemical analysis methods:

Table 2 Benefits and drawbacks of different non-destructive techniques

Applications	Benefits	Drawbacks
HSI	➢ Chemical-free approach ➢ Enables the use of spectral fingerprints to visualize different biochemical elements in a sample ➢ It contains extensive information on spectral spatial models for classification and segmentation	➢ Spectral information obtained from samples' image contain series of consecutive overlapping bands ➢ Not suitable liquid or homogenous samples ➢ Modeling and data processing are time demanding and need chemometric methods to extract important information
LLBI	➢ Non-contact approach ➢ Simple and low-cost system for the automated evaluation ➢ Feasible, economical, and rapid monitoring	➢ It has not yet been established for different varieties of climacteric fruits
FT-NIRS	➢ Have greater wave number accuracy ➢ Rapid estimation tool	➢ Sensitive to any small impurities in samples
NIRS	➢ Operate with frequent, rapid measurements and deliver analytical data from samples in real-time ➢ It permits the measurement of chemical and nonchemical (physical) properties with little to no sample preparation needed ➢ Can coupled with the appropriate multivariate model	➢ Due to the lack of selectivity, chemometric techniques must be used to retrieve important data; models that are accurate and resilient are difficult to obtain since they require a huge number of samples with substantial variability ➢ Necessarily requires prior knowledge of a certain parameter's value, which must be determined through a reference method
ENS	➢ Has the capacity to detect certain odorless compounds that usually not detectable by human nose ➢ Provide more objective results than human nose	➢ Sensor responses are influenced by humidity and temperature in a negative way
ETS	➢ More rapid and objective approach than human-based tasting panels ➢ Rapid and cost-efficient	➢ Sensitive to the fluctuation of environmental conditions such as temperature, and humidity ➢ Sometimes provide only qualitative and semi-quantitative results ➢ Sensitive and provide lower response to sucrose, caffeine, salt (NaCl), sour (HCl) and Umami (MSG)
CV	➢ Strong versatility, low cost, high efficiency, high precision and relatively simple ➢ Wide range of use (can be use in a variety of fields)	➢ It takes quite a while in visual observing processes ➢ Requires complex mechanisms

HSI Hyperspectral Imaging, *LLBI* Laser-light backscattering imaging, *FT-NIRS* Fourier transform Near infrared spectroscopy, *NIRS* Near infrared spectroscopy, *ENS* Electronic nose system, *ETS* Electronic tongue system, *CV* Computer vision time-consuming, labor-intensive, and expensive (El-Mesery et al. 2019a, 2019b). These problems are also encountered in the cacao industry and have been gradually addressed by diverse research outputs to get more advanced, sophisticated, quick, and non-destructive.

The rapid and non-destructive approach is now acknowledged as a new trend, particularly in the field of food engineering, for the purpose of quality inspection. Recently, numerous studies emerged to investigating the feasibility of this new approach in terms of quality inspection of various agricultural products such as fruits (Srivastava & Sadistap 2018; Arendese et al. 2018), vegetables (Adedeji et al. 2020), nuts (Buthelezi et al. 2019), beans, and grains during production to postharvest operations. These remarkable trends in the field of agriculture and food engineering can be used to ease the intensive and tedious work required for production and postharvest operations.

The non-destructive techniques reviewed in this paper explored applications, advantages, challenges, and potential for quality inspection, particularly in cacao. This current work also demonstrated the reliable success of rapid and noninvasive approaches for cacao quality and safety evaluation. Notwithstanding the numerous advantages acquired, each of these approaches has its drawbacks (Sect. 4) which challenge the food industry to employ this approach on a larger scale, such as industrial and commercial applications. To overcome these constraints and for this approach to be employed on a larger scale, the generalization of the hardware system to offer user-friendly and low-cost non-destructive equipment can be considered (Mohd Ali et al. 2017a).

Conclusions

This review has demonstrated the advanced applications for quality and safety evaluation of cacao using non-destructive techniques. Non-destructive techniques discussed in this work include imaging-based techniques, spectroscopic-based techniques, computer vision techniques, and other non-destructive techniques which exhibited promising performance and reliable success in the determination of different quality parameters of cacao. The most promising approach that has been established to determine the quality of cacao is spectroscopic-based techniques, particularly the FT-NIRS and imaging-based such as HSI. The variation in biochemical processes during a different phase of postharvest activities demonstrated significant changes in its hyperspectral signatures, resulting in more precise and accurate classification than any other methods that correlate spectral wavelength to a quality parameter.

To date, a few research studies on the quality evaluation of cacao have been exploited, particularly using electronic nose systems, electronic tongue, and other approaches already used in some agricultural products. Apart from this, most of the studies found in the literature are just for experimental purposes employing a minimal number of samples involved. Using this approach challenged by a large number of samples with different varieties is recommended for a more precise and robust model, which can be a good indicator for potential industrial application. It has been also applied in some of the commodities where a large number of samples/particles were involved such as grains, and other powdered products like flour where findings suggest potential industrial applications. The advancement of non-destructive technologies can increase production and enhance cacao postharvest management. As a result, it provides a wealth of data that can be accessed for real-time purposes. In brief, a rapid and non-destructive approach can be useful in evaluating and monitoring the quality and safety of cacao as it provides critical and objective understanding and visions for integrating such approaches as the final evaluation tool for cacao quality and safety in the future.

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Authors' contributions
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