Chapter

Next-Generation Tools for Nutrition-Inclusive Breeding for Cereals

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Abstract

Addressing global malnutrition requires improving the nutritional quality of major crops and promoting nutritionally rich crops. However, breeding for improving nutritional traits is challenging, particularly in the absence of rapid and precise phenotyping of these parameters. Quick phenotyping is crucial as it allows breeders to select lines with high nutritional value alongside yield and other important traits while advancing the generations. Traditionally, grain nutritional and quality assessments have relied on wet-lab analytical services, which are slow, costly, and often inaccessible. To overcome these limitations, rapid and cost-effective sensor-based technologies have emerged as a promising solution. Interdisciplinary research combining sensor technology, AI, biochemistry, and crop science has significantly advancing the grain composition analysis, and post-harvest trait evaluation. Tools like near-infrared spectroscopy (NIRS), X-ray fluorescence (XRF), and computer tomography (CT) are increasingly getting utilized to ensure quality standards in trade, nutrition, and food safety. These technologies focus on key traits precisely, time, and cost-effectively, with early findings highlighting their potential for scalable solutions. Such advancements are essential for nutrition-sensitive breeding and improving food safety, quality-based payments for farmers, and supporting global efforts against malnutrition. The swift adoption of these technologies in breeding programs, supported by public-private partnerships, is crucial for sustainable development.

Keywords: malnutrition, rapid grain quality assessment methods, sensor-based technologies, near-infrared spectroscopy, X-ray fluorescence, computed tomography, food safety

1. Introduction

Nutrition-inclusive breeding programs play a crucial role in addressing global malnutrition. In many developing and underdeveloped nations, economic growth has yet to result in better nutritional diets, leaving malnutrition a persistent issue. The effects of climate change further intensify food insecurity in these regions. In India, where over half of the population depends on agriculture for their livelihood and income, the impacts of climate change on food production and nutritional health are especially significant. Without action to promote nutrition-sensitive agriculture, the remainder of the twenty-first century could see a sharp rise in malnutrition. The United Nations designated 2023 as the International Year of Millets (IYM 2023) to raise global awareness of the nutritional and health benefits of millets, while promoting their production as climate-resilient, nutrient-dense cereals. In response, several developing nations have implemented policies and initiatives aimed at addressing the malnutrition crisis by encouraging the cultivation and consumption of these traditionally grown, nutritionally rich crops.

India's "Millet Mission" [1–3] and Kenya's "Blending Policy" [4, 5] are prominent examples of government-led initiatives aimed at addressing nutritional security. In addition, the inclusion of millets as "Nutri-Cereals" has significantly boosted their market value [6]. The Indian Council of Agricultural Research (ICAR), beyond its research and development efforts, has launched several projects in partnership with agrifood business sectors to promote nutri-cereal-based products such as cookies, ready-to-eat foods, and multi-grain flours, helping to reintroduce and popularize millets in the consumer market.

Despite these efforts, more interventions are needed to improve the overall nutritional status of the population. The challenge of ensuring access to adequate nutrition has been a central focus of agricultural research. In response, the Consultative Group on International Agricultural Research (CGIAR; One CG) is aligning crop improvement programs across institutions and regions to drive initiatives that develop nutritionally enhanced crops and advocate for nutrition-sensitive agriculture.

2. Breeding for nutrition in cereals

Crop breeding programs have expanded their focus from merely increasing yield to enhancing the quality of that yield. While boosting the productivity of calorie-dense staple cereals remains a priority, modern breeding efforts also emphasize improving the nutritional content. Achieving significant genetic gains requires an ongoing refinement of methods and strategies. For effective selection and crop improvement, it is crucial to understand both the extent and the dynamics of genotypic and non-genotypic variation, as these factors influence the potential for breeding success and adaptation to changing environmental conditions.

The yield component in cereals has been extensively investigated through research on genotype × environment × crop management (G × E × M) interactions [7–13]. However, a critical aspect that remains underexplored is the nutritional quality of cereals, which similarly responds to variations in environmental conditions and management practices. Nutritional components—especially those pertaining to both grain and stover quality—are crucial for improving human nutrition as well as livestock feed quality, which is mainly crop residue [14–17].

This gap has significant implications for the overall food system, particularly in regions where smallholder mixed crop-livestock systems are prevalent. In sub-humid, semi-arid, and arid tropics and subtropics, where the majority of the world's poorest cereal producers and consumers reside, the nutritional value of cereals plays a dual role: providing sustenance for humans and feed for livestock. The nutritional quality of staple cereals like rice, wheat, and millets directly influence human diets, as these grains often constitute the primary source of calories and essential micronutrients for vulnerable populations. At the same time, the quality of stover and crop residues, which serve as livestock feed, impacts the productivity and health of animals, further contributing to household food security through milk, meat, and other animal products.

In this context, enhancing the nutritional quality of both cereal grains and stover is essential not only for combating malnutrition among human populations but also for sustaining livestock-based livelihoods. As smallholder farmers often rely on both crops and livestock, improvements in crop nutrition can lead to a virtuous cycle of better livestock health and productivity, which in turn supports improved human nutrition through diversified diets and economic stability.

Addressing the nutritional quality of cereals thus requires a broader, integrative approach, combining advanced breeding techniques, agronomic practices, and policy interventions aimed at promoting nutrition-sensitive agriculture. This involves understanding the differential response of nutritional traits across environments and management practices and ensuring that the benefits of crop improvement reach smallholder farmers and their communities, who are most vulnerable to the impacts of malnutrition and food insecurity.

Evaluating cereals for nutritional quality traits within breeding programs poses considerable challenges due to the reliance on specialized analytical laboratories, which require advanced equipment, specific reagents, and skilled personnel [18–20]. The high costs associated with these resources, coupled with limited accessibility, further constrain breeders from routinely incorporating nutritional assessments. Traditional wet-chemistry techniques, while precise, are both time-intensive and laborious, adding to the complexity of the selection process.

This creates a significant bottleneck, as breeders often face the need for rapid decision-making to advance crop generations within a short timeframe. Considering that the development of a new crop variety can span 5–10 years, depending on the species and available resources, delays in nutritional phenotyping can prolong the process and impede the timely release of improved varieties [21–24].

Breeders also face several other challenges when working to improve the nutritional quality of crops. These include the complex genetic regulation of nutritional traits, limited genetic diversity within crop germplasm, negative linkages between nutritional and agronomic traits, environmental influences on trait expression, and varying consumer preferences and acceptance. These factors collectively hinder the development of crop varieties with enhanced nutritional profiles. However, many of these obstacles can be mitigated through the use phenotyping technologies that bridge multiple disciplines, enabling large-scale and multiple evaluation and testing of traits [25–27] when nutrition phenotyping is a significant bottleneck in terms of cost, time and precision.

To accelerate crop selection for nutritional improvement and product development, the integration of advanced phenotyping technologies is essential. These technologies, when coupled with rigorous metrics to quantify precise nutritional parameters, offer the potential for high-throughput evaluation and faster breeding cycles. This approach will be critical for achieving both the quantity and speed required to meet global demands for nutritionally superior, climate-resilient crops and accelerate genetic gains [28–32].

3. Market potential for nutritional products and quality-based payment

Introducing new crop varieties with enhanced nutritional traits presents challenges, particularly concerning consumer acceptance, market demand, and cultural preferences. Gaining consumer trust and fostering education about the benefits of these new products is critical for their successful adoption. In developing countries, however, the adoption of such improved cultivars is often slow and difficult, especially when enhanced nutritional traits do not result in direct economic benefits for farmers. The absence of economic incentives tied to the trade of bio-fortified crops hampers their widespread adoption, as smallholder farmers, who form the backbone of agricultural systems in these regions, are often excluded from premium markets. This is due to the unregulated, localized nature of grain trade, which depends heavily on intermediaries and lacks standardization. Consequently, farmers are disincentivized from investing in seed of nutritionally improved varieties.

Additionally, the prevalent issues of food adulteration and contamination further exacerbate food safety concerns, limiting access to high-quality dietary sources. In these developing regions, assessing grain quality and detecting contaminants traditionally relies on costly and time-consuming wet-lab analyses, which remain inaccessible to many underprivileged communities. The development of sensor-based technologies has the potential to revolutionize this landscape by providing quick, reliable, and cost-effective measurements of grain quality. These technologies, adaptable for use both in the field and in markets, offer rapid, environmentally friendly solutions that are tailored to decentralized market systems (**Figure 1**). By empowering smallholder farmers, vendors, and crop improvement programs alike, these innovations can facilitate better access to premium markets and enhance food safety, ultimately supporting improved livelihoods and nutrition across developing countries.

4. Need of new generation technologies for nutrition

Currently, there are only few techniques available for quick, reliable, and cost-effective field measurements of agricultural produce qualities that fit the context of trading systems in developing countries and allow smallholder farming

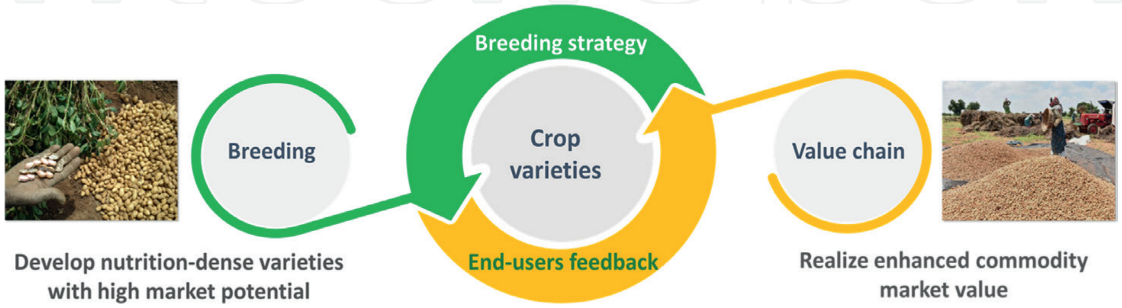

Figure 1.
Pictorial representation of the interrelationship between agrifood research and industrial sectors. The crop breeders and value chain actors are the key drivers for nutrition security-related programs. They also operate in the potential spaces for technological interventions such as integrating sensor-based crop quality assessment in their processes.

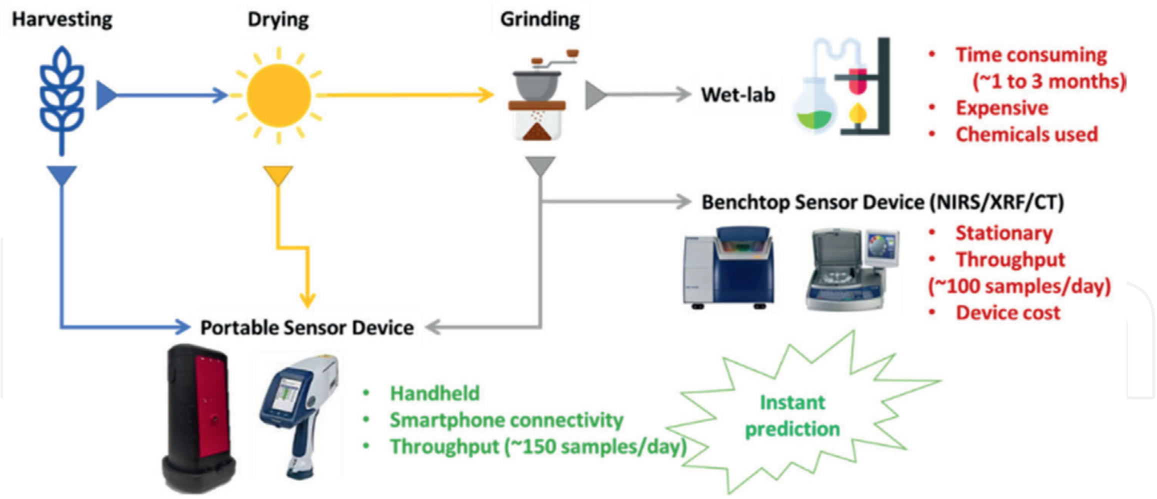

Figure 2.
A graphical representation of the potential of sensor-based technologies to be integrated in agri-research and industrial sectors.

communities to reap the benefits linked to the quality of their produce [33]. A similar situation is observed in the crop improvement programs; in this case, the laboratory facilities may be available, but these are usually not rapid enough to facilitate efficient selection within the breeding populations. For this purpose, research on translating sensors for rapid, robust, cost-effective, yet environmentally friendly grain quality analyses has been initiated (**Figure 2**) [25, 34]. Also, mobilizing sensor-based solutions like handheld devices is critical for catering to the needs of the grain-related value chain players and crop improvement programs that are primarily guided by market-demanded traits, and probably, it can trigger quality-based payment in future.

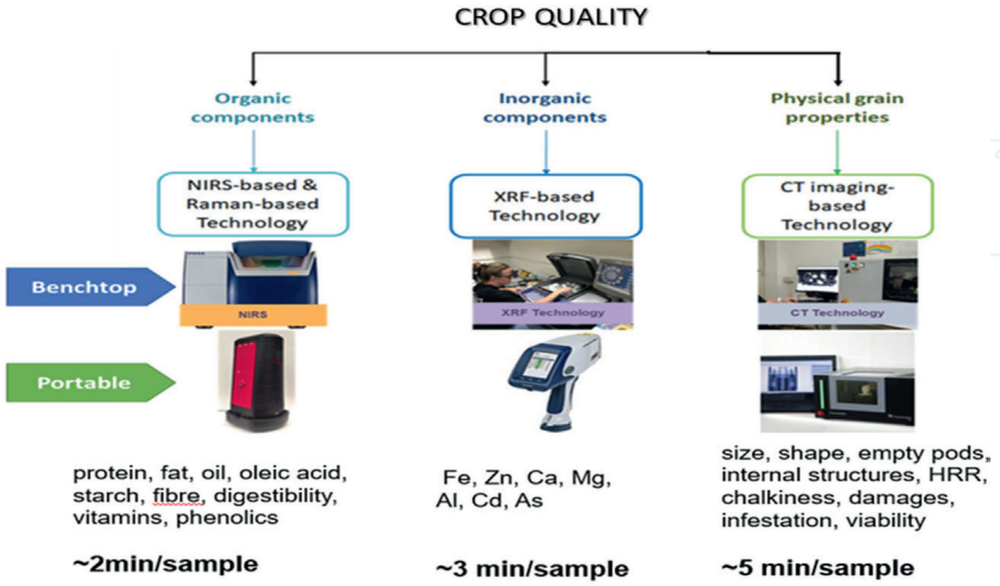

Figure 3.
A brief overview of benchtop and portable sensors (near-infrared spectroscopy, NIR; X-ray fluorescence, XRF; and X-ray computed tomography, CT) that can be deployed in breeding programs as well as value chain pipelines for rapid crop quality assessment.

NIR Instrument type	Benchtop	Portable
Application:	Screening and identification high and low nutritional composition for breeding selection and research	Rapid assessment of high nutritional samples in field and in crop value chain
Spectral range	Wide, for example, NIRS 400–2500 nm	Narrow, for example, NIRS 1100–2500
Analyses time:	less than 1 minute	1 minute
Throughput	250 whole grain samples per day 100 flour samples per day	200 whole grain samples per day 150 flour samples per day
Portability	Low and tedious	High and easy
Connectivity	Desktop computer	Mobile phone or laptop
Prediction Precision	High*	Low* (compared to benchtop but significantly accurate)
References	[32, 35, 36]	[34, 35, 37, 38]

**Depending on trait, calibration method, crop, and trait variation.*

Table 1.
An example of a benchtop and a portable near-infrared (NIR) spectrometer, X-ray fluorescence (XRF), and computed tomography (CT).

4.1 Benchtop vs. handheld sensors

The mobility of sensor technology solutions is a critical attribute, particularly when considering the needs of grain-related value chain players in the decentralized market context of developing countries. Benchtop sensors, while accurate and reliable, lack the flexibility and portability required to meet the demands of field operations and decentralized markets. In contrast, mobile sensors offer the advantage of portability and on-the-go measurements, making them well-suited for use in remote locations and field settings. This mobility is essential for catering to the needs of crop improvement programs, which are increasingly guided by market-demanded traits (**Figure 3**, **Table 1**). By providing real-time data and analysis capabilities directly in the field, mobile sensors empower stakeholders to make informed decisions swiftly and efficiently, ultimately enhancing the productivity and resilience of agricultural systems in developing countries.

5. Types of sensors

Several types of sensors are used in various fields like material science, pharma, medical, agrifood and feed industry, and agriculture. In this paper, sensors of near-infrared spectroscopy (NIRS), X-ray fluorescence (XRF), computed tomography (CT), and Raman spectroscopy are discussed (**Figure 3**) with a special focus on NIRS.

5.1 Near-infrared spectroscopy (NIRS)

NIRS operates by exposing samples to near-infrared light, which interacts with the molecular vibrations of the sample, producing a unique spectral fingerprint. The NIRS machine detects the intensity of light at various wavelengths after it has passed through or been reflected by the sample [39]. By comparing these absorption patterns to a pre-established calibration model, which correlates known chemical compositions of samples with their corresponding near-infrared absorption spectra, the NIRS machine can estimate the organic composition of nutritional traits. This technology has been successfully applied to a range of crops for organic traits like proteins, starch, fiber, fatty acids, amino acids, and fats. For instance, it has been used to estimate protein and amylose content in rice [40], lignan glucoside content in sesame [41], and oil content in safflower [42]. Both benchtop and handheld NIRS equipment are available, with benchtop models typically covering a wider wavelength range from visible light (400–2500 nm), while handheld models capture a narrower range (1100–2500 nm). The wavelengths of the sensors vary across different manufacturers of portable sensors [43].

5.2 X-ray fluorescence (XRF)

XRF, on the other hand, relies on the principle of X-ray excitation of atoms in the sample, causing them to emit characteristic fluorescent X-rays. These X-rays are then detected and analyzed to determine the elemental components like metals. XRF works with X-ray energies ranging from a few hundred electron volts to several kiloelectron volts. X-ray ray typically utilizes the band below 400 nm and are used for the prediction of inorganic nutritional traits like iron (Fe), zinc (Zn), calcium (Ca), and contaminants like aluminum (Al), arsenic (Ar), and lead (Pb). Benchtop standard XRF equipment is used to predict the inorganic composition of cereal grains, such as wheat and rice [44, 45]. The standard models were used to calibrate the position of the sample, particularly inorganic components like metals [46, 47]. The effectiveness of calibrations from both systems was evaluated by comparing the coefficient of determination [2], regression slope, and root mean square error (RMSE).

5.3 Computed tomography (CT)

CT imaging involves taking a series of X-ray images of a sample from different angles and using computer algorithms to reconstruct a 3D image. By analyzing the attenuation of X-rays as they pass through the sample, CT can provide detailed information about the internal structure, density, and morphology of the sample, making it particularly useful for non-destructive analysis of materials and biological specimens. Each of these techniques operates within specific spectral ranges, and CT imaging utilizes X-rays with energies in the range of tens to hundreds of kiloelectron volts [48]. The CT applications prove invaluable for quickly evaluating basic grain properties—such as size, shape, and damage—especially in crop species with grains covered by a hard-to-remove shell, like groundnut and rice [49, 50]. The CT equipment is also available in portable size.

5.4 Raman spectroscopy

Raman spectroscopy is a technique used in analytical chemistry and materials science to study vibrational, rotational, and other low-frequency modes in a system. It involves shining a laser light onto a sample and measuring the scattered light. The shifts in energy, known as Raman shifts, provide information about the chemical composition, crystal structure, and molecular interactions within the sample. The RS is a spectroscopic method that indirectly measures the vibrational states of samples based on the polarity of chemical bonds [51, 52]. Due to its insensitivity to water and fewer overlapped bands, RS is suitable sensor for accurate qualitative and quantitative assessment of liquid samples where NIR measurements are restricted [52]. Also, in high moisture-containing samples of grains and oilseeds, the detection of fungal and mycotoxin is easier with RS by minimizing inferences from residual components. For instance, Yuan et al. [53] utilized surface-enhanced Raman spectroscopy (SERS) to quickly detect the mycotoxin deoxynivalenol in corn, kidney beans, and oats. The SERS was also used to identify aflatoxin in maize. [54] have used RS to detect carbohydrate, fiber, carotenoid, and protein content in maize kernels.

6. Recent developments with sensors

6.1 Near-infrared spectroscopy (NIRS)

NIRS has the potential to be a highly effective tool for measuring traits associated with organic grain composition, provided the calibrations are meticulously developed and rigorously validated. For industrial applications, single-species NIR calibrations are generally preferred over multispecies calibrations because they offer greater accuracy and precision [33, 41, 42]. However, producing single-species calibrations can be challenging in certain cases, such as with “minor millet” (including pearl, finger, Kodo, Proso, Foxtail, Little millet, Sorghum, and Teff) or “orphan” legumes (such as horsegram, lablab, cowpea, mothbean, and adzuki bean), where limited diversity may hinder the development of robust calibrations. In these situations, multiple-species calibrations are used instead (**Figure 4**). For example, the performance metrics of a single-cereal equation for sorghum, built using 96 samples, were compared to those of a multiple-cereal equation constructed with 62 samples of

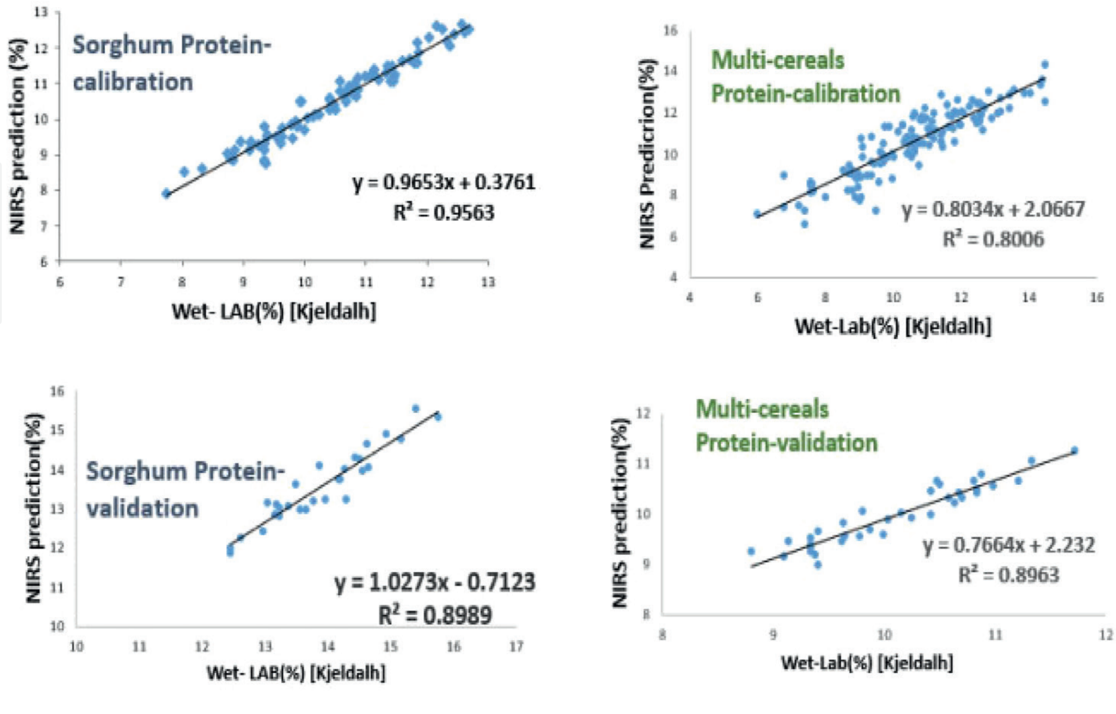

Figure 4.
Matrix of XY-scatterplots depicting the NIR-based grain protein content prediction models along with metrics for single species (sorghum) and multiple species (sorghum, pearl millet, finger millet, foxtail millet). The top panels represent the calibration or training dataset, and the lower panel represents the cross-validation dataset.

sorghum, 26 samples of pearl millet, 20 samples of finger millet, and 20 samples of foxtail millet, using various calibration methods (see **Figure 5**). The sorghum-specific calibration, which used a sufficient sample size (96) and a broad range of variation (protein: 6.7–14.2%; fat: 1.5–5.4%), predicted sorghum protein and fat more accurately (see **Figure 4**). However, the multiple-species prediction can still be applicable for sorghum, with calibration results showing R^2 values of 0.8 for protein and 0.92 for fat, and RMSE values of 0.78 for protein and 0.66 for fat. Validation metrics include R^2 values of 0.85 for protein and 0.78 for fat, RMSEP values of 0.4 for protein and 0.22 for fat, and slopes of 1.3 for protein and 0.88 for fat. This approach might be preferable for crops where the sample size and range of variation are insufficient for a single-species calibration.

6.2 X-ray fluorescence (XRF)

XRF-based technologies have traditionally been employed in heavy industrial applications, with their use in crop research only becoming more prominent in the past decade. Research on pearl millet has demonstrated significant genetic variability for iron and zinc (30–140 mg kg^{-1} Fe and 20–90 mg kg^{-1} Zn), which can be leveraged to develop high-yielding cultivars rich in these nutrients. However, previous breeding programs primarily focused on yield improvement, resulting in released cultivars and hybrids with lower Fe and Zn content [55]. Recognizing this opportunity, the All India Coordinated Research Project on Pearl Millet (AICRP-PM) of the Indian Council of Agricultural Research (ICAR) established a threshold of minimum iron (42 mg kg^{-1}) and zinc (31 mg kg^{-1}) levels for release of national varieties of pearl millet. This policy promoted biofortified pearl millet in India but also necessitates rapid assessment methods for selecting high Fe and Zn lines. Since then, XRF technology has been extensively used to screen materials, contributing significantly to alleviating malnutrition [56]. Similarly, finger millet, which is rich in calcium, required breeding efforts to select high Ca content lines. The calibration for estimating Ca content in finger millet grains using benchtop standards is currently being optimized at ICRISAT. Portable XRF is a non-destructive method that allows comparison with high-precision techniques like ICP-MS on the same sample, as demonstrated in rice

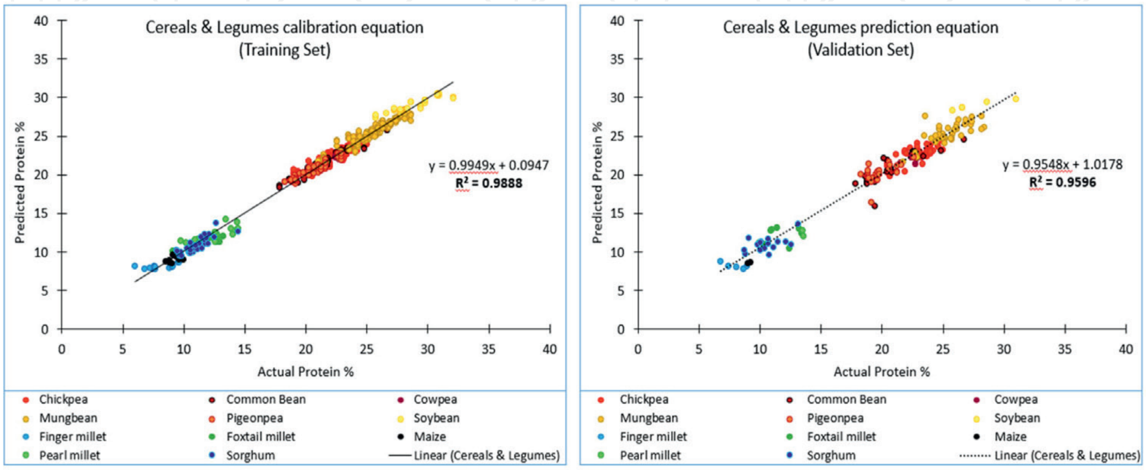

Figure 5.
Example of NIR-based protein prediction model for grain flour samples of multiple crops (cereals and legumes). The XY scatterplot of left presents the metrics of calibration or training dataset and the scatterplot of right presents the metrics for the cross-validation used for determining the robustness of the prediction model.

[45]. This report presents portable XRF measurements for As, Mn, Fe, Ni, Cu, and Zn in rice samples, comparing them with ICP-MS results for the first time. While these sensors need systematic testing on a broader range of materials, the example of pearl millet clearly illustrates that XRF application is feasible, provided the technology is rigorously tested and further developed for estimating the elemental composition of crop grain material.

6.3 Computed tomography (CT)

It has been widely used in the medical industry as well as in heavy-industry applications [57, 58]. Again, the applications for phenotyping of plant-related material are a relatively recent development [59–61]. Despite this, CT-enabled information could quickly become a game-changing factor that can enable critical information for crop improvement programs as well as for estimation of crop value in the market systems (rapid in-shell estimates such as grain weight, size and shape, damages, and shelling ratio, see **Figure 6** for example). CT has been tested to address such demand from rice and groundnut crop improvement programs where the time needed for grain threshing becomes a significant barrier in the grain evaluation during the selection process [50]. Similarly, the groundnut processing industries (e.g., Greenforest Foods Ltd., Kenya) indicated that rapid access to this information could overcome the market barrier between the small-scale producers and the large groundnut processing industries. This technology is currently being systematically tested to address these particular needs.

6.4 Raman spectroscopy

As an analytical tool, RS can provide molecular insight into mycotoxin [62, 63]. Several studies showed promising results for rapid screening of mycotoxin-contaminated grains and oilseeds and their products by Raman. Raman spectroscopy is sensitive enough to detect chemical functional groups of mycotoxin compounds and derivatives. Therefore, we expect to be able to characterize mycotoxin molecules through the molecular fingerprint of Raman and further correlate Raman information with the levels of mycotoxin contamination, as demonstrated in the quality control of cereal products [62]. Raman spectroscopy can be used to analyze the

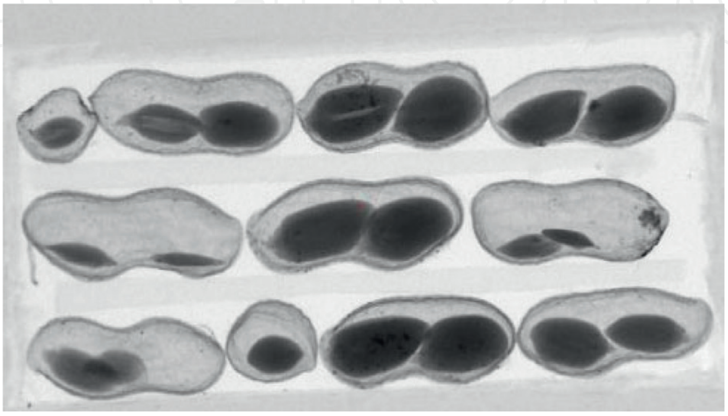

Figure 6.
A two-dimensional X-ray computed tomography image of peanuts showing variations in grain filling that translates into key traits for selection in breeding pipeline as well as for deciding the price at agri-commodity procurement centers i.e., shelling percentage and kernel weight.

chemical composition of agricultural products such as grains, fruits, and vegetables. It is increasingly recognized for its effectiveness in assessing plant health, crop quality, and species, as well as detecting plant maturity, ripeness, freshness, nutritional content, presence of contaminants or pesticides, abiotic stresses, and diseases [64–66]. It supports rapid phenotyping and digital plant selection, facilitating early detection of bacterial infections, fungal diseases, insect invasions, and other pathogens in greenhouses and fields [64, 66, 67].

7. NIRS as emerging powerful technology for nutritional breeding pipeline

Technological tools are available to greatly enhance the nutritional value of breeding programs. However, enhanced nutrition in any breeding program might only be achieved if the screening of nutritional traits is handy, economical, and fast. NIRS is one of the most proven tools to measure organic grain and stover composition like protein, fat, starch, amino acid, polyphenols, phytic acid, amino acid, *in vitro* digestibility, metabolizable energy, fiber content, etc., in large sample size where chemical analysis is time consuming and expensive [33, 42, 68]. NIRS has been advanced to sensitize the variations across year, location, variety, time of sowing, etc. [69]. NIRS technology holds promising power for nutrition research by accelerating the data collection in crop improvement and understanding the physiology of nutritional traits at low production cost to effectively select the best for human and animal nutrition.

8. Physiological basis of nutritional trait: Case study in sorghum

Sorghum, a versatile crop cultivated worldwide for food, feed, and biomass, holds significant importance for ensuring food security, particularly in vulnerable semi-arid agricultural regions. Despite its crucial role, much of the genetic diversity of sorghum, preserved in the ICRISAT gene bank in India with approximately 40,000 accessions, remains underexplored, particularly regarding variations in grain and stover nutritional composition. The grain nutritional composition of 3000 sorghum accessions with NIRS-based benchtop reveals intriguing insights in **Figure 7**. The density gradient map of each group of accessions, including historic, exotic collection, and ICRISAT Sorghum collections, exhibited distinct positions along this relationship. Noteworthy is the trend observed in historical collections, which typically displayed higher fat content and lower protein content than other groups. Also, recently developed materials in breeding programs are able to increase the protein content and reduce fat. These findings shed light on the diverse genetic variation for nutritional traits available for sorghum germplasm and underscore the importance of further exploration and utilization of this genetic diversity in breeding programs aimed at enhancing nutritional traits.

Accessing and leveraging the vast variability in crop traits is imperative for driving tangible improvements through crop breeding endeavors. Beyond merely identifying this variability, a deeper understanding of the underlying biological processes and their interactions with the environment is essential. In one of the studies ([1]; unpublished), the stover and grain quality of 18 sorghum genotypes across various factorial agronomic treatments (water stress, planting density, and nitrogen fertilization). NIR-based leaf, stem, and panicle quality assessments during early growth stages showed prediction potential for grain nitrogen content as well as stover quality at crop

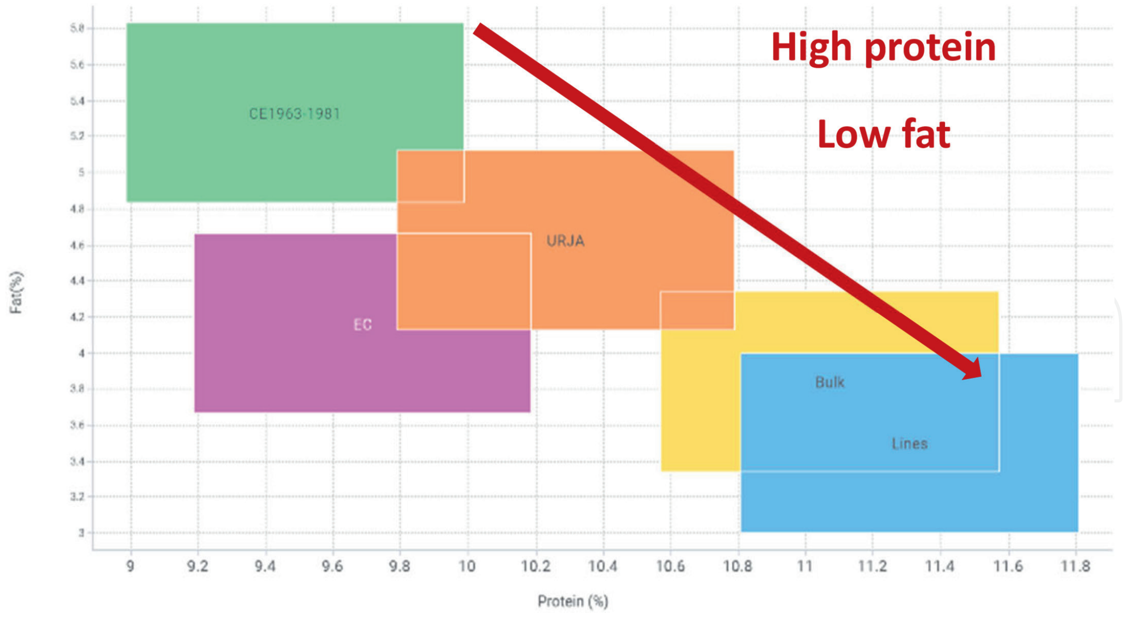

Figure 7.
Graphical representation of the negative relationship between grain protein and fat content in sorghum germplasm collections of ICRISAT.

maturity (**Figure 8**). In addition, significant correlations between leaf senescence and stover quality suggest the potential for indirect field assessments of stover quality based on visual scoring. The interconnectedness of various plant traits and their implications for crop nutritional quality suggests avenues for accelerating breeding efforts through indirect methods.

Furthermore, functional links between plant allometry at maturity and grain nutrient composition offers insights into predicting grain nutritional content based

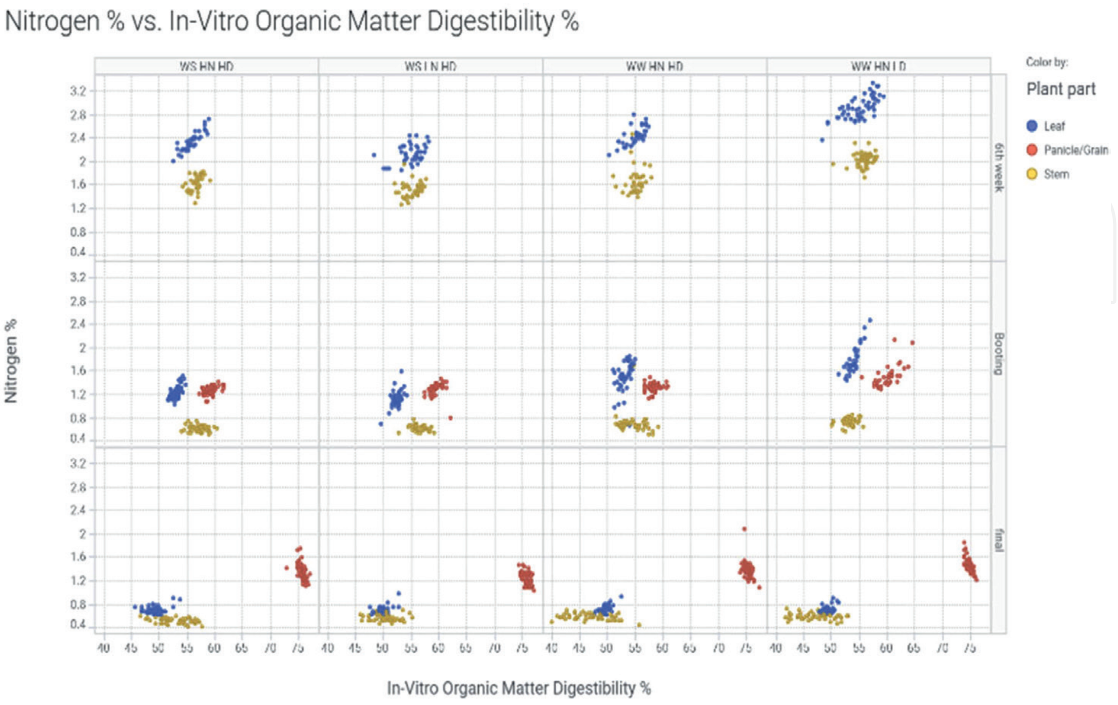

Figure 8.
Matrix of XY-scatter plots indicating relationships between grain nitrogen content and in vitro organic matter digestibility in different plant parts depicted through different colors (leaf: blue, panicle and grain: red; stem: yellow).

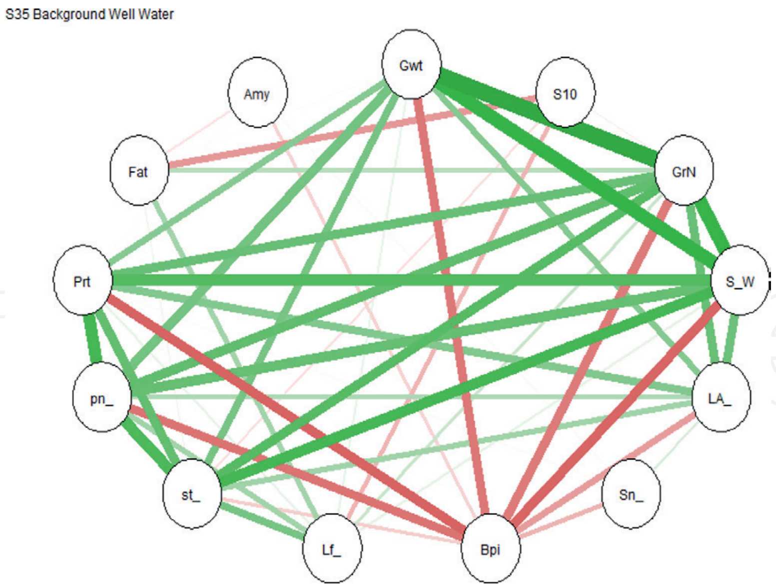

Figure 9.
Correlation networks depicting the interrelationships between different agronomic and nutritional traits (Gwt = grain weight [g plant−1], GrN = grain number per panicle, S_W = stover weight [g plant−1], LA_ = canopy leaf area [cm2], Sn_ = senescence score [0–100%], Bpi = Biomass partitioning index, Lf_ = Leaf in-vitro organic matter digestibility [w/w%], st_ = Stem in-vitro organic matter digestibility [w/w%], pn_ = panicle or grain in-vitro organic matter digestibility [w/w%], Prt = grain protein content [w/w%], Fat = grain fat content [w/w%], and Amy = grain amylose content [w/w]. Green lines and red lines in correlation networks represent positive and negative correlations respectively. Strength of each line indicates the strength of correlation between the pairs. Values within each line in a correlation network represent correlation coefficients.

on plant parameters ([32], unpublished, **Figure 9**). Additionally, the observed synergistic associations between stover productivity and quality, as well as grain quality, as illustrated in **Figure 9**. The correlation network analysis revealed interrelationships among various parameters, including grain weight (both per plant and per hectare), grain size, grain number, stover weight (per plant and per hectare), maximum leaf area (at booting stage), leaf area index, senescence score, biomass partitioning index (BPi), and the nutritional composition of leaves, stems, and panicles. This method aids in visualizing and identifying patterns, revealing key variables and potential causal relationships within complex datasets. For instance, biomass partitioning (Bpi) is negatively associated with grain weight (Gwt), grain numbers (GrN), stover weights, protein content (Prt), and panicle weight. Additionally, grain weight (Gwt) is positively associated with grain numbers (GrN) and stover weight, while negatively associated with biomass partitioning (Bpi). Furthermore, protein content (Prt) is positively associated with stover quality, grain numbers, panicle weight, and grain weight, and negatively associated with biomass partitioning (Bpi). Moreover, stover quality is positively associated with protein content, grain weight, grain numbers, and stem weight, and negatively associated with biomass partitioning (Bpi). These findings underscore the importance of integrating multidimensional data from field experiments with advanced analytical techniques to inform and expedite crop improvement strategies aimed at enhancing nutritional qualities.

9. Conclusion

Nutrition-inclusive breeding and value chains necessitate adoption of reliable, robust, and applicable tools for rapid phenotyping of crop nutritional composition.

Especially for making informed decisions on the choice of crop, farm management, product development, and processing, delivery for human as well as animal nutrition and well-being. Advances in instrumentation, computational power, digital networking, and internet access can be tailored to the agricultural sector and further optimized for different contexts and stakeholders. This book chapter focuses on the sensor-based technologies for crop quality assessment in crop breeding programs, but this can further be connected upstream and downstream with remote sensing and agrometeorological information, econometric modeling, socio-cultural preferences, commodity pricing and trading, marketing and certification, integrated farm advisory tools, etc. Agricultural development requires multidimensional systemic interventions considering diverse players, constraints, and opportunities. Sensors are one such tool that can be explored and integrated at various stages of farming to enable stakeholders to measure quantity as well as quality, which is essential for streamlining nutrition-related breeding and crop value chains. Such efforts are imperative to accelerate the development of nutritionally dense grain-crop products, particularly for the most vulnerable agricultural systems and stakeholders. Incorporating sensor-based technologies like NIRS and XRF into regular breeding programs and crop value chains holds promise for accelerating nutrition selection alongside productivity. At the same time, it is essential to understand the complexities of nutrition physiology and cascade mechanisms for fully exploiting these tools in breeding endeavors. Establishing global networks that unite experts from various fields is crucial for developing and implementing sensor-based technologies in agrifood research and industry. This also involves co-development of sensors (i.e., testing, calibration, and validation of sensors) with different stakeholders and for the development of nutritionally dense safe products tackling malnutrition.

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References

[1] Choudhury PP. Odisha millet mission, another nutritious cereal for healthy living. Agriculture and Food: E-Newsletter. 2023;**5**(2):223-225

[2] Kumari P, Thakur A, Sankhyan NK, Singh U. Millet production and consumption in India and their nutritional aspects. Just Agriculture. 2023;**3**(5):46

[3] Verma HP, Verma A. Chhattisgarh millet mission. Just Agriculture E-Magazine. 2023;**3**(5):67-68. Available from: https://justagriculture.in/files/newsletter/2023/january/91.%20Chhattisgarh%20Millet%20Mission.pdf

[4] Melesse MB, Tessema YM, Manyasa E, Hall A. An enabling environment for the national flour blending policy: A food systems analysis. In: Breisinger MK, Mbuthia J, Njuki J, editors. Part 6: Toward more Sustainable Food Systems, Chapter 16 Food Systems Transformation in Kenya: Lessons from the Past and Policy Options for the Future. Washington, DC: Intl Food Policy Res Inst; 2023. pp. 409-432. DOI: 10.2499/9780896294561_16

[5] Poole N, Donovan J, Kariuki S, Rutsaert P, Ibba MI, Bentley A. Flour blending can mitigate food insecurity and economic stress. Global Food Security. 2024;**41**:100758

[6] WPI. Wholesale Price Index. 2018. Available from: www.eaindustry.nic.in

[7] Seyoum A. Multi-environment evaluation and genotype x environment interaction analysis of sorghum [*sorghum bicolor* (L.) Moench] genotypes in highland areas of Ethiopia. Journal of Environmental Geology. 2021;**5**(3):1

[8] Motlhaodi T, Bryngelsson T, Chite S, Fatih M, Ortiz R, Geleta M. Nutritional variation in sorghum [*Sorghum bicolor* (L.) Moench] accessions from southern Africa revealed by protein and mineral composition. Journal of Cereal Science. 2018;**1**(83):123-129

[9] Wirnas D, Sopandie D, Tesso T. Genotypes X environment interaction effect on nutritional quality of sorghum lines in Indonesia. Ekin Journal of Crop Breeding and Genetics. 2015;**1**(2):26-31

[10] Cakmak I. Enrichment of cereal grains with zinc: Agronomic or genetic biofortification. Plant and Soil. 2008;**302**:1-7

[11] White PJ, Broadley MR. Biofortification of crops with seven mineral elements often lacking in human diets–iron, zinc, copper, calcium, magnesium, selenium and iodine. New Phytologist. 2009;**182**(1):49-84

[12] Graham RD. Breeding for nutritional characteristics in cereals. Advances in Plant Nutrition. 1984;**1**:57-102

[13] Swamy BM, Marathi B, Ribeiro-Barros AI, Ricachenevsky FK. Development of healthy and nutritious cereals: Recent insights on molecular advances in breeding. Frontiers in Genetics. 2021;**12**:635006

[14] Blümmel M, Duncan AJ, Lenné JM. Recent advances in dual purpose rice and wheat research: A synthesis. Field Crops Research. 2020;**15**(253):107823

[15] Upadhyaya HD, Vetriventhan M, Are AK, Azevedo VCR, Wang YH. Sorghum Germplasm for enhanced productivity and nutrition. In: Tonapi VA, Talwar HS, Are AK, Bhat BV,

Reddy CR, Dalton TJ, editors. Sorghum in the 21st Century: Food – Fodder – Feed – Fuel for a Rapidly Changing World. Singapore: Springer; 2020. pp. 101-123. DOI: 10.1007/978-981-15-8249-3_5

[16] Parissi Z, Irakli M, Tigka E, Papastylianou P, Dordas C, Tani E, et al. Analysis of genotypic and environmental effects on biomass yield, nutritional and antinutritional factors in common vetch. Agronomy. 2022;**12**(7):1678

[17] Gangashetty PI, Yadav CB, Riyazaddin M, Vermula A, Asungre PA, Angarawai I, et al. Genotype-by-environment interactions for starch, mineral, and agronomic traits in pearl millet hybrids evaluated across five locations in West Africa. Frontiers in Plant Science. 2023;**23**(14):1171773

[18] Aguilar EG, Albarracín GD, Uñates MA, Piola HD, Camiña JM, Escudero NL. Evaluation of the nutritional quality of the grain protein of new amaranths varieties. Plant Foods for Human Nutrition. 2015;**70**:21-26

[19] Mallick SA, Azaz K, Gupta M, Sharma V, Sinha BK. Characterization of grain nutritional quality in wheat. Indian Journal of Plant Physiology. 2013;**18**:183-186

[20] AOAC. Official Methods of Analysis, Association of Official Analytical Chemists. 15th ed. USA: AOAC International; 1990

[21] Fassio A, Fernández EG, Restaino EA, La Manna A, Cozzolino D. Predicting the nutritive value of high moisture grain corn by near infrared reflectance spectroscopy. Computers and Electronics in Agriculture. 2009;**67**(1-2):59-63. DOI: 10.1016/j.compag.2009.03.001

[22] Nurit E, Tiessen A, Pixley KV, Palacios-Rojas N. Reliable and inexpensive colorimetric method for determining protein-bound tryptophan in maize kernels. Journal of Agricultural and Food Chemistry. 2009;**57**(16):7233-7238. DOI: 10.1021/jf901315x

[23] Rosales A, Galicia L, Oviedo E, Islas C, Palacios-Rojas N. Near-infrared reflectance spectroscopy (NIRS) for protein, tryptophan, and lysine evaluation in quality protein maize (QPM) breeding programs. Journal of Agricultural and Food Chemistry. 2011;**59**(20):10781-10786. DOI: 10.1021/jf201468x

[24] Porep JU, Kammerer DR, Carle R. On-line application of near infrared (NIR) spectroscopy in food production. Trends in Food Science and Technology. 2015;**46**(2):211-230. DOI: 10.1016/j.tifs.2015.10.002

[25] Williams P, El-Haramein FJ, Hani N, Safouh R. Crop quality evaluation methods and guidelines. Crop quality evaluation methods and guidelines. In: Technical Manual (ICARDA). International Center for Agricultural Research in the Dry Areas. 2nd ed. Vol. 14. Syria: Aleppo; 1988. p. 142

[26] Wu F, Rodricks JV. Forty years of food safety risk assessment: A history and analysis. Risk Analysis. 2020;**40**(S1):2218-2230

[27] Balkir P, Kemahlioglu K, Yucel U. Foodomics: A new approach in food quality and safety. Trends in Food Science and Technology. 2021;**108**:49-57

[28] Agelet LE, Hurburgh CR Jr. A tutorial on near infrared spectroscopy and its calibration. Critical Reviews in Analytical Chemistry. 2010;**40**:246-260. DOI: 10.1080/10408347.2010.515468

[29] Workman J, Weyer L. Practical Guide and Spectral Atlas for Interpretive

Near-Infrared. Boca Raton: CRC; 2012. DOI: 10.1201/b11894

[30] Villamuelas M, Serrano E, Espunyes J, Fernández N, López-Olvera JR, Garel M, et al. Predicting herbivore faecal nitrogen using a multispecies near-infrared reflectance spectroscopy calibration. PLoS One. 2017;**12**(4):e0176635. DOI: 10.1371/journal.pone.0176635

[31] Rukundo E. Stochastic model of rural agribusiness supply chain: A case study of Gatsibo District. Modern Economy. 2022;**13**:370-396. DOI: 10.4236/me.2022.133021

[32] Chadalavada K, Anbazhagan K, Ndour A, Choudhary S, Palmer W, Flynn JR, et al. NIR instruments and prediction methods for rapid access to grain protein content in multiple cereals. Sensors. 2022;**22**(10):3710. DOI: 10.3390/s22103710

[33] De Alencar Figueiredo LF, Davrieux F, Fliedel G, Rami JF, Chantereau J, Deu M, et al. Development of NIRS equations for food grain quality traits through exploitation of a core collection of cultivated sorghum. Journal of Agricultural and Food Chemistry. 2006;**54**(22):8501-8509. DOI: 10.1021/jf061054g

[34] Dos Santos CA, Lopo M, Páscoa RN, Lopes JA. A review on the applications of portable near-infrared spectrometers in the agro-food industry. Applied Spectroscopy. 2013;**67**(11):1215-1233

[35] Yang J, Li J, Hu J, Yang W, Zhang X, Xu J, et al. An interpretable deep learning approach for calibration transfer among multiple near-infrared instruments. Computers and Electronics in Agriculture. 2022;**192**:106584. DOI: 10.1016/j.compag.2021.106584

[36] Alamu EO, Nuwamanya E, Cornet D, Meghar K, Adesokan M, Tran T, et al. Near-infrared spectroscopy applications for high-throughput phenotyping for cassava and yam: A review. International Journal of Food Science and Technology. 2021;**56**(3):1491-1501

[37] Folli GS, Santos LP, Santos FD, Cunha PH, Schaffel IF, Borghi FT, et al. Food analysis by portable NIR spectrometer. Food Chemistry Advances. 2022;**1**:100074

[38] Beć KB, Grabska J, Siesler HW, Huck CW. Handheld near-infrared spectrometers: Where are we heading? NIR News. 2020;**31**(3-4):28-35

[39] Pasquini C. Near infrared spectroscopy: Fundamentals, practical aspects and analytical applications. Journal of the Brazilian Chemical Society. 2003;**14**:198-219

[40] Himmelsbach DS, Barton FE, McClung AM, Champagne ET. Protein and apparent amylose contents of milled rice by NIR-FT/Raman spectroscopy. Cereal Chemistry. 2001;**78**(4):488-492

[41] Kim KS, Park SH, Shim KB, Ryu SN. Use of near-infrared spectroscopy for estimating lignan glucosides contents in intact sesame seeds. Journal of Crop Science and Biotechnology. 2007;**10**(3):185-192. DOI: 10.1007/978-94-007-0723-8_13

[42] Elfadl E, Reinbrecht C, Claupeina W. Development of near infrared reflectance spectroscopy (NIRS) calibration model for estimation of oil content in a worldwide safflower germplasm collection. International Journal of Plant Production. 2012;**4**(4):259-270. DOI: 10.22069/IJPP.2012.709

[43] Beć KB, Grabska J, Huck CW. Principles and applications of miniaturized near-infrared (NIR) spectrometers. Chemistry–A European

Journal. 2021;**27**(5):1514-1532. DOI: 10.1002/chem.202002838

[44] Peruchi LC, Nunes LC, de Carvalho GG, Guerra MB, de Almeida E, Rufini IA, et al. Determination of inorganic nutrients in wheat flour by laser-induced breakdown spectroscopy and energy dispersive X-ray fluorescence spectrometry. Spectrochemical Acta Part B: Atomic Spectroscopy. 2014;**100**:129-136. DOI: 10.1016/j.sab.2014.08.025

[45] Fleming DE, Foran KA, Kim JS, Guernsey JR. Portable x-ray fluorescence for assessing trace elements in rice and rice products: Comparison with inductively coupled plasma-mass spectrometry. Applied Radiation and Isotopes. 2015;**104**:217-223. DOI: 10.1016/j.apradiso.2015.07.014

[46] Chen ZW, Gibson WM, Huang H. High definition X-ray fluorescence: Principles and techniques. X-Rays Optics and Instrumentation. 2008;**2008**:1-10. DOI: 10.1155/2008/318171

[47] Marguí E, Queralt I, De Almeida E. X-ray fluorescence spectrometry for environmental analysis: Basic principles, instrumentation, applications and recent trends. Chemosphere. 2022;**303**:135006. DOI: 10.1016/j.chemosphere.2022.135006

[48] Kak AC, Slaney M. Principles of computerized tomographic imaging. Society for Industrial and Applied Mathematics. 2001;**20**(23):114-133

[49] Hu W, Zhang C, Jiang Y, Huang C, Liu Q, Xiong L, et al. Nondestructive 3D image analysis pipeline to extract rice grain traits using X-ray computed tomography. Plant Phenomics. 2020;**2020**:1-12. DOI: 10.34133/2020/3414926

[50] Domhoefer M, Chakraborty D, Hufnagel E, Claußen J, Wörlein N, Voorhaar M, et al. X-ray driven peanut trait estimation: Computer vision aided agri-system transformation. Plant Methods. 2022;**18**(1):76. DOI: 10.1186/s13007-022-00909-8

[51] Long DA. Raman spectroscopy. New York. 1977;**1**:310

[52] Yang D, Ying Y. Applications of Raman spectroscopy in agricultural products and food analysis: A review. Applied Spectroscopy Reviews. 2011;**46**(7):539-560. DOI: 10.1080/05704928.2011.593216

[53] Yuan J, Sun C, Guo X, Yang T, Wang H, Fu S, et al. A rapid Raman detection of deoxynivalenol in agricultural products. Food Chemistry. 2017;**221**:797-802. DOI: 10.1016/j.foodchem.2016.11.101

[54] Krimmer M, Farber C, Kurouski D. Rapid and noninvasive typing and assessment of nutrient content of maize kernels using a handheld Raman spectrometer. ACS Omega. 2019;**4**(15):16330-16335. DOI: 10.1021/acsomega.9b01661

[55] Rai KN, Yadav OP, Govindaraj M, Pfeiffer WH, Yadav HP, Rajpurohit BS, et al. Grain iron and zinc densities in released and commercial cultivars of pearl millet (Pennisetum glaucum). Indian Journal of Agricultural Sciences. 2016;**86**(03):11-16

[56] Govindaraj M, Rai KN, Cherian B, Pfeiffer WH, Kanatti A, Shivade H. Breeding biofortified pearl millet varieties and hybrids to enhance millet Markets for Human Nutrition. Agriculture. 2019;**9**(5):106. DOI: 10.3390/agriculture9050106

[57] Fuchs T, Keßling P, Firsching M, Nachtrab F, Scholz G. Industrial applications of dual X-ray energy

computed tomography (2X-CT). In: Güneş O, Akkaya Y, editors. Nondestructive Testing of Materials and Structures. Vol. 6. Dordrecht: RILEM Bookseries, Springer; 2013. pp. 97-103. DOI: 10.1007/978-94-007-0723-8_13

[58] De Chiffre L, Carmignato S, Kruth JP, Schmitt R, Weckenmann A. Industrial applications of computed tomography. CIRP Annals. 2014;**63**(2):655-677. DOI: 10.1016/j.cirp.2014.05.011

[59] Walter A, Liebisch F, Hund A. Plant phenotyping: From bean weighing to image analysis. Plant Methods. 2015;**11**(14):1-1. DOI: 10.1186/s13007-015-0056-8

[60] Gomez FE, Carvalho G, Shi F, Muliana AH, Rooney WL. High throughput phenotyping of morpho-anatomical stem properties using X-ray computed tomography in sorghum. Plant Methods. 2018;**14**:1-3. DOI: 10.1186/s13007-018-0326-3

[61] Wu D, Guo Z, Ye J, Feng H, Liu J, Chen G, et al. Combining high-throughput micro-CT-RGB phenotyping and genome-wide association study to dissect the genetic architecture of tiller growth in rice. Journal of Experimental Botany. 2019;**70**(2):545-561. DOI: 10.1093/jxb/ery373

[62] Sohn M, Himmelsbach DS, Barton FE. A comparative study of Fourier transforms Raman and NIR spectroscopic methods for assessment of protein and apparent amylose in rice. Cereal Chemistry. 2004;**81**(4):429-433

[63] Ma CY, Lee PD. FT-Raman spectroscopy and its applications in cereal science. Cereal Chemistry. 2002;**79**(2):171-177. DOI: 10.1094/CCHEM.2002.79.2.171

[64] Payne WZ, Kurouski D. Raman-based diagnostics of biotic and abiotic stresses in plants. A Review. Frontiers in Plant Science. 2021;**11**:616672. DOI: 10.3389/fpls.2020.616672

[65] Saletnik A, Saletnik B, Puchalski C. Raman method in identification of species and varieties, assessment of plant maturity and crop quality—A review. Molecules. 2022;**27**(14):4454. DOI: 10.3390/molecules27144454

[66] Farber C, Kurouski D. Raman spectroscopy and machine learning for agricultural applications: Chemometric assessment of spectroscopic signatures of plants as the essential step toward digital farming. Frontiers in Plant Science. 2022;**13**:887511. DOI: 10.3389/fpls.2022.887511

[67] Gan Q, Wang X, Wang Y, Xie Z, Tian Y, Lu Y. Culture-free detection of crop pathogens at the single-cell level by micro-raman spectroscopy. Advanced Science. 2017;**4**(11):1700127. DOI: 10.1002/advs.201700127

[68] Kahriman F, Egesel CÖ. Development of a calibration model to estimate quality traits in wheat flour using NIR (near infrared reflectance) spectroscopy. Research Journal of Agricultural Science. 2011;**43**(3):392-400

[69] Dardenne P. Stability of NIR spectroscopy equations. NIR News. 1996;**7**(5):8-9. DOI: 10.1255/nirn.380