International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 07 Issue 05 May 2024
DOI: 10.47191/ijcsrr/V7-i5-104, Impact Factor: 7.943
IJCSRR @ 2024
www.ijcsrr.org

Non-destructive Near-infrared Hyperspectral Imaging in Food Technologies with a Focus on Monitoring Seed Viability

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ABSTRACT: Seed qualities including viability and germination significantly influence the quantity and the quality of harvest. Technological means to assess seed qualities and attributes of seed-derived food products are varied. This paper highlights the use of infrared hyperspectral imaging (NIR- HSI) in food quality control, authentication, safety, process monitoring, shelf-life prediction, ingredients analysis, allergens detection and food sorting and grading. It also shows a particular application of NIR-HSI for the monitoring of nutrient content of sprouts and germinated seeds for industrial processing of foods with high nutritional values. The paper further reviews the applications of NIR-HSI to predict seed viability and germination. The non-destructive, rapid, and high-throughput capability of NIR-HSI were demonstrated through research works combining the NIR-HSI technology with chemometrics tools to reach more than 90% prediction rate. These relatively high rates may depend on the storage conditions or the stringency of the artificial aging conditions applied to parts of the seeds. However, the NIR-HSI has also proven efficient using naturally aged seeds with the prediction rates up to 90% correct classification, demonstrating the high capability of the technology. In combination with advanced chemometrics tools, some components of emerging technologies such as traditional machine learning and deep learning models have been added to increase the efficiency of NIR_HSI. Overall, the research works reviewed in this paper and which cover several food crops and food products showed that NIR-HSI is set to reach new heights in monitoring seed viability for improved seed stock management, crop production and innovation in the food industry.

KEYWORDS: Seed viability, germination, hyperspectral imaging, near infrared spectroscopy, food technologies

INTRODUCTION

Seed viability translating to the capacity of the seed to germinate is vital for humans with regards to food and nutrition security, animal feeds, medicinal plants and the equilibrium of ecosystems. Germination is the first step which determines the survival, the growth and the quality of plant production. Thus, seed viability and seed germination are key themes of scientific research globally. They are studied by several fields of science which address different questions, but which all contribute to the understanding and knowledge of these two complex biological phenomena (1, 2, 3, 4). While seed viability defined as the ability of the embryo to germinate measures whether individual seeds are dead or alive within a seed lot, seed germination is the capacity of the seed to produce a satisfactory plant under favorable conditions. On the food and nutrition security aspects, seed germination is not only required for continued crop production, it is also important for the industrial production of highly nutritious and organoleptic food products processed directly using germinated seeds and sprouts. Indeed, pre-germination appears to be an easy and cost-effective way of enhancing the nutritional values of edible seeds (5, 6, 7, 8, 9).

In relation to the importance of germination for humans as stated above, the number of scientific fields, technologies, informatics tools and statistical approaches to tackle various aspects of seed viability and germination for food production and food processing is increasing. Among these technologies, near infrared spectroscopy (NIR) and near infrared hyperspectral imaging (NIR-HSI) are increasingly used to get greater insights into seed viability and germination. Near infrared spectroscopy is a technology for measuring chemical constituents of intact biological materials without destroying the materials, thus providing the possibility to use the intact materials for other purposes (e.g. germination for seeds). It is based on the vibration properties (overtones and combination vibrations) of major X-H chemical bonds within organic molecules (C–H, O–H and N–H) and their interactions with infrared radiation. Hyperspectral imaging (HSI) is a high throughput imaging technology which allows to target the entire materials under study, or to choose specific regions of interest within the materials. Both approaches (NIR and HSI) can be combined to obtain the near infrared hyperspectral imaging (NIR-HSI) approach for a non-destructive, rapid and high throughput determination of the spectral (seed chemical composition), and the spatial information (regions of interest) from a sample (10, 11, 12). The NIR-HSI technology acquires thousands of spectra from the entire sample or from a fraction of the sample from images obtained in the near infrared (780-2500 nm), contrary to the classical NIR which acquires only one spectrum representing the average of the analyzed sample in the same spectral range (13, 11). One of the main advantages of NIR-HSI over NIR is to allow the simultaneous assessment of the spectral and spatial distribution of the chemical composition of samples (10, 11, 12, 14, 15), therefore giving the possibility to discriminate different parts of the same sample according to their chemical composition. Further, NIR-HSI images allow a direct and qualitative comparison of two or more samples (16, 17). The present review addresses the use of near infrared hyperspectral imaging in food technologies and highlights specific details on the use of the technology in the key steps of food production, namely seed viability and germination.

Near infrared hyperspectral imaging in food technologies

The near infrared hyperspectral imaging is applicable to solid samples as well as liquid samples, thus the variety of its applications in food technologies to a large range of food products. Several studies using the near infrared hyperspectral technology have contributed to various areas of food technologies including food quality control and authentication (18, 19, 20, 21), food safety assessment (22, 23, 24, 25), food process monitoring and optimization (26, 27, 28), food shelf-life prediction (29, 30), food ingredients analysis (31, 32), food allergens detection (33, 34), and food sorting and grading (35). These research works showed that NIR-HSI covers notable areas of food technologies. In the industrial processing of sprouts and germinated seeds used directly as raw materials to make highly nutritious food products, NIR-HSI is efficiently used to monitor and to optimize the levels of key nutrients and organoleptic attributes. The applications of NIR-HSI to germinated seed and sprouts in the food industry follow the same procedures as in the applications to determines nutrient content of non-germinated seeds (36, 37, 38, 39), with the added aspect of monitoring the evolution of the nutrient content over time during the germination process.

Near infrared hyperspectral imaging to assess seed viability and germination

In this area, the objective of most research works using NIR-HSI is to predict seed viability and seed germination using a non-destructive, rapid, and high-throughput method to screen seed lots for crop improvement, commercial purposes, and germplasm conservation as summarized in Table 1. This applies also to the monitoring of the germination process from the imbibition of the seed to the visible germination stage when the radicle emerges.

Table 1: Research works on the use of near infrared spectroscopy and near infrared hyperspectral imaging to assess seed viability and seed germination

Food crop	Aims of the research	Technological, statistical and informatics approaches	State of the seeds used	Results of the best classification model	Authors
Bottle gourd	Classify seed germination ability	NIR-HSI and Partial least squares discriminant analysis (PLSDA)	Stored during one year	More than 75 %	17
Spinach	Predict viability	NIR and Extended canonical variates analysis (ECVA)	Artificially aged	More than 85 %	40
	Determine seed viability	NIR-HSI and Support vector machine (SMV)	Naturally aged	At 90%	45
Muskmelon	Predict viability and vigor	NIR-HSI and Partial least squares discriminant analysis (PLSDA)-SR	Artificially aged	More than 90 %	41
Watermelon	Establish a continuous process to visualize seed viability	NIR-HSI and Partial least squares discriminant analysis (PLSDA)	Naturally aged	More than 90 %	48

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Tomato	Predict viability	NIR and Modified partial least squares (MPLS), Partial least squares (PLS), Principal component regression (PCR)	Artificially aged	*R^2=0.939 **RPD=3.96,	42
Maize/Corn	Predict seed germination rate	NIR and Partial least squares regression (PLSR)	Stored from three months to two years under uncontrolled room conditions	***RMSEP=8.88%	43
	Identify the viability	NIR-HSI and Multi-scale 3D convolutional neural, Network (multi-scale 3DCNN, YOLOv7 and Mask R-CNN	Artificially aged	More than 90 %	49
Rice	Determine seed viability and vigor	NIR-HSI and Deep learning and conventional methods	Naturally aged	More than 85 %	47
	Determine vigor	NIR-HSI and Convolutional neural network (CNN)	Artificially aged	At 90 %	50
	Determine seed vigor	NIR-HSI and Self-built Convolutional neural network CNN (Self-built CNN), ResNet18, Partial least squares discriminant analysis (PLSDA), Support vector machine (SMV)	Artificially aged	More than 99 %	44
Wheat	Predict vigor during storage	Vis/NIR, SWIR HSI and Partial least-squares regression (PLS-R)	Artificially aged	R^2=0.921 ****RMSE=5.137%	46
Soybean	Classify seed vigor levels	NIR and Partial least squares discriminant analysis (PLSDA)	Naturally aged and Artificially aged	More than 85 %	51

Notes: *R^2: Coefficient of determination; **RPD: Ratio of Performance to Deviation; ***RMSEP: Root mean standard error of prediction; ****RMSE: Root mean square error

The search for the most suitable wavelengths is done through the analysis of the best models for the prediction and the classification of seed viability and germination using NIR and NIR-HSI data. The studies compared different models using chemometrics tools (statistical analyses of chemical data), and selected the most important variables of classification for the construction of the best models (Table 1). They also determined the factors underlying the differences between viable and non-viable seeds, or between germinated and non-germinated seeds by identifying the most discriminating wavelengths associated with seed chemical content. To date, emerging technologies such as artificial intelligence and related approaches combined with improved chemometrics tools are augmenting the throughput and the efficiency of NIR-HSI for the production of more nutritious edible seeds, and for the processing, uniformity, authentication and safety of derived food products.

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CONCLUSION

Mature edible seeds reach a maximum germination potential which gradually decreases after harvest, depending on the duration and conditions of storage. The loss of germination power over time affects all types of seeds to various extents. Overall, advances in current research indicate that the use of NIR and NIR-HSI technology and the development of prediction models for seed viability has led to fast, high-throughput, non-destructive and cost-effective assessment of seed germination. This further leads to improved management of seed lots for seedbanks, crop production, commercial and industrial uses. In the majority of the previous studies using classical methods, seeds were manually sorted into viable and non-viable after artificial aging, or separated into germinated and non-germinated (non-viable) after the germination tests. Thereafter, substantial technical efforts were deployed to develop the methodologies for NIR or NIR-HSI prediction models. Current research are mostly focused on the classification of naturally aged seeds for a direct application of the findings. Prediction models obtained from such studies have greater potential to remove non-viable seeds from seed lots thereby avoiding the misclassification caused by human subjectivity. Thus, the applications of near infrared hyperspectral imaging have increased substantially the efficiency of monitoring the viability and the germination of edible seed for crop production, industrial processing and quality control of food products. The versatility and the accuracy of this technology make it a prime tool for food technologists and researchers aiming at improving crop production and innovating in the food industry. The technology is garnering significant attention from researchers because of its cross-border nature involving several fields of science and technologies as summarized in the present review. With the increasing inputs of emerging technologies such as artificial intelligence with multiple data processing and models, NIR-HSI is set to revolutionize traditional seed management practices for an even greater role in seed viability assessment and food technologies.

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Cite this Article: Nadège Aurelie N'dri-Aya, Irié Vroh-Bi (2024). Non-destructive Near-infrared Hyperspectral Imaging in Food Technologies with a Focus on Monitoring Seed Viability. International Journal of Current Science Research and Review, 7(5), 3480-3486