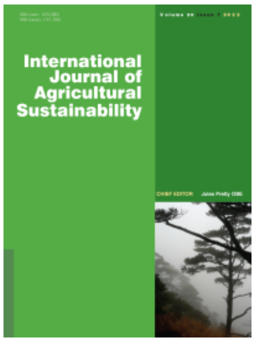

International Journal of Agricultural Sustainability

ISSN: 1473-5903 (Print) 1747-762X (Online) Journal homepage: www.tandfonline.com/journals/tags20

Optical imaging for food grain quality evaluation – recent advances and future perspectives

Opeyemi Micheal Ageh , Norhashila Hashim, Rosnah Shamsudin, Hasfalina Che Man , Maimunah Mohd Ali , Daniel I. Onwude & Abhishek Dasore

INTERNATIONAL JOURNAL OF AGRICULTURAL SUSTAINABILITY
2025, VOL. 23, NO. 1, 2569166
https://doi.org/10.1080/14735903.2025.2569166

Taylor & Francis
Taylor & Francis Group

RESEARCH ARTICLE

OPEN ACCESS Check for updates

Optical imaging for food grain quality evaluation – recent advances and future perspectives

Opeyemi Micheal Ageh[a], Norhashila Hashim[a,b], Rosnah Shamsudin[c], Hasfalina Che Man[a,b], Maimunah Mohd Ali[d], Daniel I. Onwude[e] and Abhishek Dasore[a]

[a]Faculty of Engineering, Department of Biological and Agricultural Engineering, Universiti Putra Malaysia, Serdang, Malaysia; [b]Faculty of Engineering, SMART Farming Technology Research Centre (SFTRC), Universiti Putra Malaysia, Serdang, Malaysia; [c]Faculty of Engineering, Department of Process and Food Engineering, Universiti Putra Malaysia, Serdang, Malaysia; [d]Faculty of Science and Technology, Department of Food Sciences, Universiti Kebangsaan Malaysia, Bangi, Malaysia; [e]Empa Swiss Federal Laboratories for Material Science and Technology, ETH Zurich, St. Gallen, Switzerland

ABSTRACT

Optical imaging techniques have gained widespread popularity in grain quality evaluation due to their non-destructive nature, rapid analysis, and ability to provide detailed information about various grain properties. This review highlights recent advancements in optical imaging technologies, including hyperspectral imaging (HSI), multispectral imaging (MSI), RGB imaging, fluorescence imaging (FI), thermal imaging (TI), and ultraviolet imaging (UVI) along with their future perspectives. These techniques are discussed in terms of their principles, applications, and potential for non-destructive assessment of grain quality parameters such as composition, defects, and contamination. A comparative analysis of these techniques is provided, emphasizing their precision, application areas, and limitations. Challenges such as calibration model development, illumination variability, and the complexity of image analysis are critical for widespread adoption to construct robust and generalised models. Despite these challenges, integrating these imaging techniques offers significant opportunities for improving grain sorting, storage, and processing. By providing comprehensive and objective data, these technologies have the potential to revolutionize grain quality monitoring and enhance postharvest management practices, enabling greater efficiency and reduced costs.

ARTICLE HISTORY
Received 22 August 2024
Accepted 27 September 2025

KEYWORDS
Optical imaging; food grain; grain quality evaluation; non-destructive testing; hyperspectral imaging; artificial intelligence

1 Introduction

Grain quality evaluation is a critical aspect of the grain industry, as it impacts the safety, nutritional value, and marketability of grain products (Ndubisi et al., 2022). The quality evaluation encompasses the assessment of a range of physical and chemical properties, including size, shape, colour, moisture content, protein levels, and the detection of defects or contaminants (Neerja & Renu, 2019). Traditionally, grain quality assessment relies on destructive techniques, such as proximate analysis and sensory evaluation, which involve altering or destroying samples through grinding, sieving and chemical analysis (Liu et al., 2022). These methods are time-consuming, labour-intensive, and expensive, with notable drawbacks including low accuracy, high costs, and prolonged analysis durations (Wang et al., 2019).

In recent years, optical imaging techniques have emerged as a promising tool for non-destructive grain quality evaluation (Wang et al., 2018). These techniques offer advantages such as high accuracy, rapid analysis, and cost-effectiveness while simultaneously providing information on multiple quality parameters (Gan et al., 2021). They also enable high-precision measurement and the ability to evaluate a large number of samples efficiently (Zhou et al., 2019). Various types of radiation, including visible, near-infrared (NIR), and mid-infrared (MIR), are utilized to obtain detailed images of grain samples and analyse their physical and chemical properties (Liu et al., 2017).

CONTACT Norhashila Hashim norhashila@upm.edu.my Department of Biological and Agricultural Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia

Optical imaging systems have undergone significant developments in recent years. It has been increasingly used in agriculture for various applications, including crop monitoring, disease detection, and yield estimation (Talaviya et al., 2020). However, challenges such as high costs, system complexity, and limited accessibility hinder widespread adoption, particularly for small-scale farmers. There is an urgent need for accurate, portable, and cost-effective optical imaging systems that integrate real-time machine learning (ML) models for field-based grain quality assessment. This review aims to provide a comprehensive overview of the latest advancements in optical imaging techniques for grain quality evaluation, focusing on their principles, applications, and limitations. Additionally, it explores their potential to address critical challenges, including the growing demand for high-quality grain products and the need for optimized storage and handling practices. By consolidating state-of-the-art developments, this review seeks to inform decision-making and drive innovation in the agricultural and grain sectors.

2 Quality of grain

Grains are an important source of nutrition for animals and humans. They are widely cultivated and consumed around the world, making them an important commodity for both food and feed industries. The quality of grains can be assessed based on various external and internal parameters. External quality encompasses physical attributes such as grain size, shape, colour, and texture. These characteristics significantly influence the appearance and sensory properties of final products. For instance, grain size and shape affect cooking time and texture, while colour and texture contribute to visual appeal and mouthfeel. Internal quality refers to the chemical properties of the grains that can affect their nutritional value and processing characteristics. Moisture content, protein content, and starch content affect the cooking quality and the grain's nutritional value, while contaminants such as mycotoxins, heavy metals, and pesticide residues affect their safety and overall quality (Zahra et al., 2022).

Grains are essential sources of nutrients and have several physicochemical and physiological properties. Physiochemical properties are those properties of a substance that can be observed or measured without changing the chemical composition of the substance, while physiological properties refer to the characteristics or functions of the plant that are related to its growth, development, and metabolism. These properties are important in understanding how plants respond to various environmental factors, and how they carry out essential functions such as photosynthesis, water, nutrient uptake, and reproduction. They are composed of a range of components, including proteins, carbohydrates, lipids, minerals and vitamins which contribute to their overall composition. Physiochemical quality encompasses the physical aspects of grains, as well as chemical characteristics, including moisture, protein, fat, fibre, carbohydrates, and vitamins. These characteristics can be affected by environmental conditions, such as temperature and humidity, as well as by genetic variability. Physiological quality, on the other hand, pertains to the functional characteristics of grains, including their germination capacity, sprouting potential, and storage viability (Poornima & Shantha, 2023). Influenced primarily by genetic factors, this aspect of quality is crucial for ensuring a stable and dependable food supply. Different studies have extensively examined the physicochemical and physiological traits of various grains, highlighting notable differences across varieties in these properties. For example, Li et al. (2022) reported that some grain varieties possess higher protein content, while others demonstrate increased resistance to specific diseases, making them more suitable for particular food production purposes. Evaluating both physicochemical and physiological parameters is essential when selecting grains to ensure optimal performance and consistent product quality. Ultimately, both external and internal grain qualities play a critical role in determining their suitability for diverse food and feed applications.

3 Optical imaging systems and image processing

Optical imaging systems have been increasingly applied in agriculture to collect environmental data and support decision-making processes (Zhongzhi, 2019). This technique employs different wavelengths of light to capture images of plants, offering valuable insights into their health, growth, and yield. Optical imaging has also been applied to grain analysis, such as assessing chlorophyll content and canopy structure in crops, which serves as an indicator of plant productivity and potential yield (Zhang et al., 2022). One of the primary applications of optical imaging in agriculture is plant stress measurement. For example, this technique has been employed to study the effects of drought and heat stress on crops, such as wheat and corn (Li et al., 2022). By detecting changes in light absorption and reflectance in plant tissues, these methods can identify early signs of stress before visible symptoms manifest. Optical imaging systems, integrated with computer vision (CV) and pattern recognition, enable comprehensive analysis of plant growth from germination to root development (Lube et al., 2022). These systems offer high-quality tools for reliably analysing various plant structures, including seed shape and colour intensity (Zhang et al., 2018). Moreover, when combined with artificial intelligence (AI), these methods are cost-effective and straightforward to implement (Teena et al., 2016).

3.1 System components

Optical imaging works by capturing images of objects using light. The primary hardware components of an optical imaging system include a light source, optical lenses, optical filters, a detector, and electronic components for processing the acquired data, as depicted in Figure 1. The light source illuminates the target area, and the detector measures the scattered light (Yoon et al., 2020). The light source can be a laser or a broadband light source, such as a lamp or an LED. The lens focuses the light onto the detector, while optical filters remove unwanted wavelengths to enhance image contrast (Vollmer, 2021). The detector, typically a charge-coupled device (CCD) or complementary metal-oxide-semiconductor (CMOS) image sensor, captures the light and converts it into an electrical signal. This signal is processed to form an image (Scheffer, 2007). The behaviour of light in these systems is determined by its interaction with the object being imaged, while the hardware components are responsible for capturing and processing the light information.

Optical lenses are critical components in an optical imaging system, as they collect and focus light onto the imaging sensor or detector. A lens consists of a curved glass element that refracts light in a specific direction. Some lens components are fixed within the barrel, while others can be adjusted to facilitate functions such as zooming, focusing, and image stabilisation. Key lens features include lens speed, focal length, and focusing mechanism (Qandil et al., 2019).

Optical filters selectively transmit or block certain wavelengths or ranges of light. These filters are made from materials, such as glass, plastic, and thin films, with material choice depending on spectral requirements, durability, and cost. Glass filters, while more robust and efficient at transmitting light, are typically more expensive than plastic filters. Thin film filters, created by depositing thin layers of various materials onto a substrate, offer precise control over spectral characteristics. Optical filters are classified based on

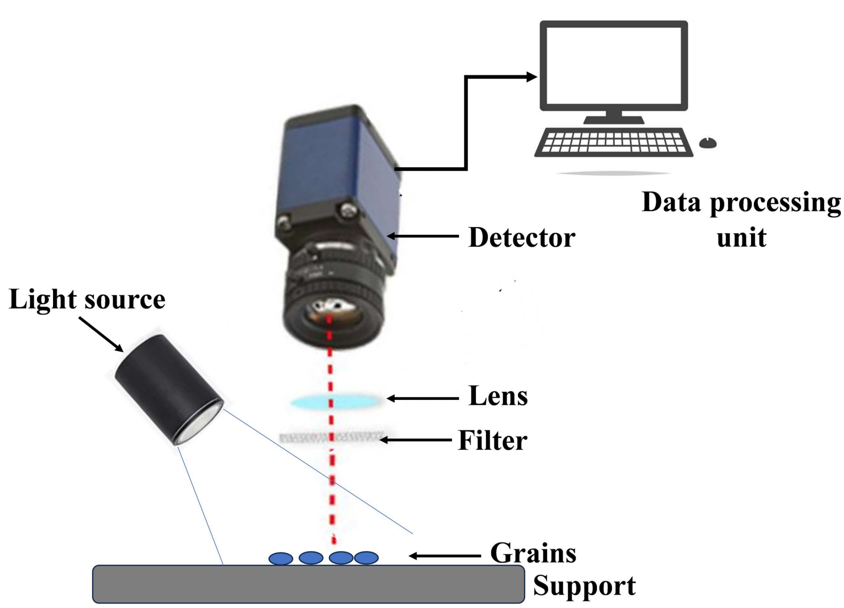

Figure 1. Schematic representation of an optical imaging system.

their spectral transmission or absorption characteristics into types such as bandpass filters, long-pass filters, short-pass filters, neutral density filters, and colour filters (Liu et al., 2021). Neutral density filters reduce light intensity across a broad spectral range without altering its colour, making them particularly useful in applications like photography and light management. By controlling light intensity, these filters facilitate longer exposure times or larger apertures. Colour filters, on the other hand, selectively transmit or block specific wavelengths of light to modify colour. Commonly used in photography and cinematography, they create colour effects or enhance colour balance. Depending on the application, colour filters can be classified as subtractive, which block certain wavelengths, or additive, which transmit specific wavelengths (Guo et al., 2021).

3.2 Fundamental mechanism

The behaviour of light in optical imaging is governed by the principles of geometrical optics and wave optics. Geometrical optics focuses on the path of light rays as they traverse different materials, explaining how light forms images. In contrast, wave optics examines light as a wave, describing phenomena such as diffraction and interference. When light interacts with an object, it is absorbed, scattered, or transmitted, depending on the object's properties and the wavelength of the light. The detected light is then converted into an image or quantitative data using suitable imaging modalities, which can be analysed to extract valuable insights about the sample's structure, function, or molecular composition (Umul, 2008). This interaction between light and matter provides critical information about the object's structure and condition. Berger et al. (2018) emphasized that the fundamental principle of optical imaging lies in this interaction. As light passes through a transparent medium, a portion is absorbed by the medium and converted into heat, while the rest is scattered in various directions. The intensity and wavelength of the scattered light depend on factors such as the size, shape, and refractive index of the scattering particles (Lin et al., 2021). Optical imaging systems capture the light that interacts with the sample, which may include transmitted light that has passed through the object and emitted light from processes like fluorescence. This combination of transmitted and emitted light forms the basis for generating detailed images or datasets (Umul, 2008).

3.3 Image processing techniques

Image processing is a crucial step in preparing raw image data for CV applications, ensuring an optimal format of data for subsequent analysis. It enhances image quality by removing distortions and emphasising essential features, thereby improving the performance of AI and ML models in grain quality evaluation. Key preprocessing techniques include resizing, which standardizes image dimensions for consistency across datasets, and grayscaling, which reduces computational load and complexity by converting colour images to grayscale. Noise reduction techniques such as Gaussian blur and median filtering improve image clarity by minimising distortions. Normalisation adjusts pixel intensity values to a defined range, typically 0 to 1, enhancing analytical efficiency. Binarization, achieved through thresholding, simplifies images into black-and-white representations for easier feature extraction. Contrast enhancement techniques, like histogram equalisation, improve visibility by adjusting the distribution of brightness (Jimoh et al., 2025).

Despite these advancements, challenges remain in ensuring the reliability of optical images for grain quality assessment. Distortions such as noise interference, uneven lighting, low contrast, and improper exposure can degrade image clarity. Effective preprocessing techniques address these inconsistencies, improving data integrity and the accuracy of downstream analysis. A well-structured preprocessing workflow is essential, as multiple techniques may be required depending on imaging modality and application. Poor preprocessing choices can negatively impact AI model performance, leading to unreliable predictions. While many techniques are universally applied, their implementation varies based on the imaging system and data type.

For instance, HSI generates complex, high-dimensional datasets that require spectral denoising and dimensionality reduction to optimize spectral band management (Zhu et al., 2025). In contrast, RGB images, being simpler, typically undergo basic filtering, colour correction, and segmentation to address lighting inconsistencies and enhance grain texture or defect visibility. FI often employs background subtraction and thresholding to distinguish fluorescence signals from background surrounding noise.

4 Application of optical imaging for grain quality evaluation

In recent years, optical imaging systems have been increasingly utilized to assess grain quality. These systems are employed to identify and classify grains based on product type and variety, as well as to help detect the presence of diseases and infestation. A summary of the various applications of optical imaging in grain quality evaluation is provided in Table 1.

4.1 RGB imaging

RGB imaging refers to the use of the red, green and blue colour model to capture and represent images. The RGB colour model is device-dependent, meaning different devices can detect or reproduce RGB values differently (Steve, 2006). RGB imaging has been applied in the agricultural industry for tasks such as detecting disease or insect damage, identifying nutrient deficiencies, evaluating the quality of agricultural products, and sorting and grading fruits and vegetables. It is a cost-effective, non-destructive, rapid, accurate, and automatic system, that can be applied in both laboratory and field settings (Mohd Ali et al., 2020). Moreover, RGB imaging system process and analyse digital images to determine specific attributes, such as shape or colours which facilitate object recognition through automatic processing. The system electronically perceives and evaluates an image by emulating human vision (Bachik et al., 2020). A typical RGB imaging system for agricultural applications includes an imaging sensor, a light source for illumination, a computer or processor for running image processing algorithms, a holder or platform for positioning the plant sample, and an LCD screen for displaying output data, as shown in Figure 2.

RGB imaging is a rapidly growing field with many applications in the monitoring and evaluation of grain quality. This technology has been used to monitor grain quality during production and to facilitate accurate evaluation of the final product for sale or consumption. RGB imaging systems can detect defects in grains, such as discolouration or insect damage, which are difficult to identify with the human eye (Aznan et al., 2021). For monitoring grain quality during production, RGB imaging systems can quickly identify issues with crop yield such as pest infestations or fungal growths (Lu et al., 2017). By analysing images taken from various angles along with colour information gathered through spectroscopy techniques (Choudhury, 2014), these systems can assess crop health without human intervention. This data can then be used by farmers or producers to make informed decisions about crop management to optimize yields while minimising losses due to pests or disease outbreaks (Lu et al., 2017). Additionally, when evaluating finished products prior to sale or consumption, RGB imaging plays a vital role in ensuring consistent standards across multiple batches.

When image analysis is integrated with ML algorithms specifically tailored to each food type, these systems can detect not only physical defects but also subtle variations in taste profiles capabilities that would ordinarily require expert human assessment (Ireri et al., 2019). This capability allows producers to achieve greater consistency throughout their supply chain while reducing labour costs traditionally associated with manual inspection before products reach the marketplace (Bao & Li, 2020). Ghyar and Birajdar (2017) showed that RGB imaging, combined with SVM and ANN classifiers, could accurately detect pests in rice, achieving classification rates of 93% and 88%. Abu Bakar et al. (2018) successfully detected rice leaf blast early and differentiated infection severity levels using image processing. Suman and Dhruvakumar (2015) classified various rice diseases with an SVM classifier and an RGB camera. In maize, Guo et al. (2021) monitored crop growth and identified Tasselling Dates (TD) with a Root Mean Square Error (RMSE) of 5.77 days, while Ge et al. (2016) found strong correlations between RGB image data and maize biomass at early growth stages ($R^2 > 0.95$). Overall, RGB imaging is a valuable tool for grain quality monitoring, disease detection, and damage assessment.

4.2 Visible and near-infrared imaging

Visible (VIS) and NIR imaging are powerful technologies used to monitor grain quality, assess grain processing, and ensure food safety as illustrated in Figure 3. Visible imaging provides a direct view of

Table 1. Summary and analysis of various optical imaging techniques for different types of grain evaluation.

Detector	Grains	Application	Equipment	Wavelengths/image resolution	Image processing and data analysis	Reference
RGB imaging	Rice	Identification of Rice Blast (RB) and Brown Spot (BS) diseases using digital RGB images	Smartphone Camera (iPhone 7 Plus)	1080 × 1920 pixels at 401 ppi	K-means clustering on RGB-based colour indices to classify diseases	Terensan et al. (2024)
	Rice	Automatic classification of diseased and healthy rice leaves	Digital camera	NA	Feature extraction using GLCM, colour moments, Genetic Algorithm-based feature selection, SVM, and ANN for classification	Ghyar and Birajdar (2019)
	Rice	Classification of rice samples	Smartphone (iPhone 11) with Lightbox 1	3024 × 4032 pixels	Feature extraction from RGB and CIELab colour space, ANN classification, PCA, Cluster Analysis	Aznan et al. (2021)
	Rice	Identification and diagnosis of rice diseases	Canon EOS 5D Mark III	5760 × 3840 pixels	CNN-based classification using MATLAB R2012a and the CNNs toolbox	Lu et al. (2017)
	Maize	Identification of Tasselling Date (TD) using spectral and textural information	DJI Phantom 4 Pro V2.0	5472 × 3648 pixels	Spectral and textural analysis using VI and GLCM, Index generation using IAFWM, TD identification, and RMSE calculation	Guo et al. (2021)
	Maize	Plant phenotyping, estimation of plant area and water use	Basler Camera (LemnaTec 3D Scanalyzer System)	2454 × 2056 pixels	Statistical & correlation analysis, WUE calculation	Ge et al. (2016)
MSI	Maize	Detection of zearalenone content in maize	VideometerLab (Videometer A/S, Hørsholm, Denmark)	19 wavelengths: 405, 435, 450, 470, 505, 525, 570, 590, 630, 645, 660, 700, 780, 850, 870, 890, 910, 940, 970 nm	Genetic Algorithm and Backpropagation Neural Network (GA -BPNN).	Li et al. (2022)
	Maize	Grading of whole white maize kernels	VideometerLab2 (Videometer, Hørsholm, Denmark)	19 wavelengths: 375, 405, 435, 450, 470, 505, 525, 570, 590, 630, 645, 660, 700, 780, 850, 870, 890, 940, 970 nm	PCA, PLS-DA	Sendin et al. (2018)
	Spinach seeds	Discriminate between seed sizes, predict germination ability and germ length	VideometerLab MSI system	19 wavelengths: 395, 430, 450, 470, 505, 565, 590, 630, 645, 660, 700, 850, 870, 890, 910, 920, 940, 950, 970 nm	PLS-DA, variable importance for projection (VIP), first-order statistics, Haralick texture features	Shetty et al. (2012)
	Rice seeds	Determine and classify transgenic and non-transgenic rice seeds	VideometerLab MSI system	19 wavelengths: 405, 435, 450, 470, 505, 525, 570, 590, 630, 645, 660, 700, 780, 850, 870, 890, 910, 940, 970 nm	PCA, PLSDA, LS-SVM, PCA-BPNN, canonical discriminant analysis (CDA), morphological features extraction	Liu et al. (2014)
FI	Maize (Zea mays L.)	Study the effects of chlorsulfuron residue and cadmium on enzymatic activity and photosynthetic apparatus	FluorCam FC 1000-H, PSI, Brno, Czech Republic	Fluorescence parameters of chlorophyll: Fv/Fm, NPQ, qP, Fv′/Fm′, Rfd	ANOVA, fluorescence parameter analysis (Fv, Fm, NPQ, qP, Rfd, Fv/Fm)	Zhao et al. (2018)
	Snap beans (Blue Lake 274)	Investigate translocation of Rhodamine B (Rh-B) for crop	High-resolution CMOS camera (Sony Alpha 5000) with UV filter (Zeta UV L41); UV-A	UV (385 nm) and visible; Spectral range: 350–1050 nm; Spectral	Image processing with Fiji ImageJ for noise removal, thresholding, and	Su et al. (2019)

Table 1. (*Continued*)

Detector	Grains	Application	Equipment	Wavelengths/image resolution	Image processing and data analysis	Reference
		signalling and weed discrimination.	LEDs (385 nm) and white LEDs for illumination; Custom tablet interface for control.	resolution: 0.28 nm; Image resolution: 5456 × 3632 pixels.	ROI measurements; ANOVA and Tukey HSD for statistical analysis.	
	Sorghum	Validate the PS2 FI system in a field setting and compare with a handheld fluorometer.	Field-deployed gantry-based phenotyping system (TERRA-REF field scanalyzer) equipped with chlorophyll FI system; Handheld fluorometer.	Fluorescence: 650–800 nm; Saturating light: >3000 µmol in ~1 s.	Correlation analysis between imaging system and handheld fluorometer; Temporal tracking of fluorescence changes over 7 days due to DCMU treatment.	Herritt et al. (2020)
VIS and NIR imaging	Milled Rice	Non-destructive measurement of amylose content in rice, improved accuracy using NIR spectra and physical properties from the VIS grain segregator	Omega Analyser G BR–5000 NIR transmittance spectrometer; ES–1000 VIS grain segregator; Solid Prep III auto-analyser for reference amylose content (ACref)	NIR: 850–1048 nm (2-nm increment, path length 30 mm) VIS: NA	PLS regression for NIR spectra analysis MLR for combining NIR spectra and physical properties	Olivares Dí et al. (2019)
HSI	Wheat kernels	Classification of FHB-damaged wheat kernels (sound, mildly, moderately, severely damaged) using HSI and a deep learning network	SOC710-E hyperspectral imager; Dark box with four 75 W halogen neodymium lamps; Lifting platform; Computer with SRANL710 software	HSI: 374–1030 nm (245 bands after noise removal) Image size: 1392 × 1392 pixels, exposure time 78 ms	Feature selection using ReliefF, UVE, RFrog, SFLA; Classification models using KNN, SVM, CNN (LeNet and VGG16); Hyperparameter optimisation using ASSDN and Auto-Keras	Yipeng et al. (2022)
NIR HSI	Barley Kernels	Detect fungal infections (A. glaucus, Penicillium spp.) and Ochratoxin A contamination in stored barley kernels	NIR camera (Indium Gallium Arsenide), Liquid Crystal Tunable Filters (LCTFs), Tungsten halogen lamps, Data processing system (LabVIEW, MATLAB)	Wavelength range: 1000–1600 nm, 61 wavelengths at 10 nm intervals, Image resolution: 640 × 480 pixels, 12-bit MSI	PCA for data reduction, Median filter for dead pixel removal, Segmentation with bwlabel function, Histogram and statistical features extraction, Linear, quadratic, and Mahalanobis discriminant classifiers, SAS PROC DISCRIM for model development	Sentilkumar et al. (2016)
HSI	Barley seeds	Identify barley seed varieties to ensure seed purity	NIR enhanced camera (Image-N17E), line scan imaging spectrometer (Specim V10E), motorized platform, notebook computer (Dell with SpecVIEW software)	Spectral range: 866.4–1701.0 nm, Image resolution: 320 × 256 pixels, Wavelengths: Full spectrum from 866.4–1701.0 nm	Preprocessing: SNV, MSC, Savitzky-Golay first derivative; Feature selection: SPA; Discriminant models: KNN, SVM, RF; Evaluation: accuracy, Kappa values	Sun et al. (2021)
	Rice	Classification of rice varieties, combat adulteration	Vis/NIR HSI system (SOC710VP, USA) Imaging spectrograph with a 12-bit CCD; Data collection unit with SRANL710 software	Spectral range: 400–1000 nm Image resolution: 1392 × 1392	Spectral preprocessing: MSC, SNV, S-G smoothing, S-G1; Feature extraction: spectroscopy, morphology (11 parameters), texture (190 parameters) - PCA for dimensionality reduction - PCANet (deep learning network)	Weng et al. (2020)

(*Continued*)

Table 1. (*Continued*)

Detector	Grains	Application	Equipment	Wavelengths/image resolution	Image processing and data analysis	Reference
					for classification - Comparison with KNN and RF models	
TI	Rice grains (Japonica and Indica) and mixtures (in grain or flour format)	Classification of rice types and detection of adulteration	Thermographic camera (Optris PI Model 450) - Closed glass flask (Raypa Model BAD–4); Transparent plastic spectroscopic cuvette (1 cm light path)	Image resolution: 382 × 288 pixels Temperature range: ~34°C to 30 °C during cooling	Deep learning for feature selection and classification; Thermal profile extraction from cooling process; Video frame extraction (every 0.15 s) for colour mapping and temperature differences; Feature selection, classification stages, and model estimation with CNN	Estrada-Pé et al. (2021)
X-ray imaging	Wheat grains	Quantification of morphological changes during wheat grain development	Phoenix Nanotom 180NF µCT scanner, Gelatin capsule, paraffin, hydrated paper, MATLAB and Fiji software for image processing	Resolution: 4.4 to 15 µm/pixel (varies by scan) Voxel size: 16-bit TIFF format Image slices stored in 16-bit TIFF	Segmentation of grain and compartments for volume analysis; 3D image reconstruction; Morphometric analysis; Quantification of crease depth and shape using CPDA detector; Image processing via global thresholding, region selection	Le et al. (2019)
UVI	Wheat	Multispectral autofluorescence imaging to identify the tissular origin of particles via autofluorescence profiles.	Nikon Multizoom AZ100M, DS-Ri1 Camera	Wavelengths: UV (U1: 325–375 nm, U2: 360–370 nm), Visible (BL: 450–490 nm, GR: 510–560 nm). Image Resolution: 2.74 µm/pixel. FOV: 3.5 × 2.8 mm^2	PCA, MANOVA with ANOVA functions. Normalisation of intensities for data comparison.	Corcel et al. (2016)

Fm: maximum fluorescence; FOV: field of view; Fv: variable fluorescence; Fv/Fm: maximum quantum efficiency of photosystem II; GLCM: grey-level co-occurrence matrix; GLCM: grey-level co-occurrence matrix; MANOVA: multivariate analysis of variance; MLR: multiple linear regression; MSC: multivariate scatter correction; NPQ: non-photochemical quenching; PCA: principal component analysis; PLS: partial least squares; PLS-DA: partial least squares discriminant analysis; qP: photochemical quenching; Rfd: fluorescence decline ratio; SNV: standard normal variate; SPA: successive projections algorithm; S-G: savitzky-golay; WUE: water use efficiency.

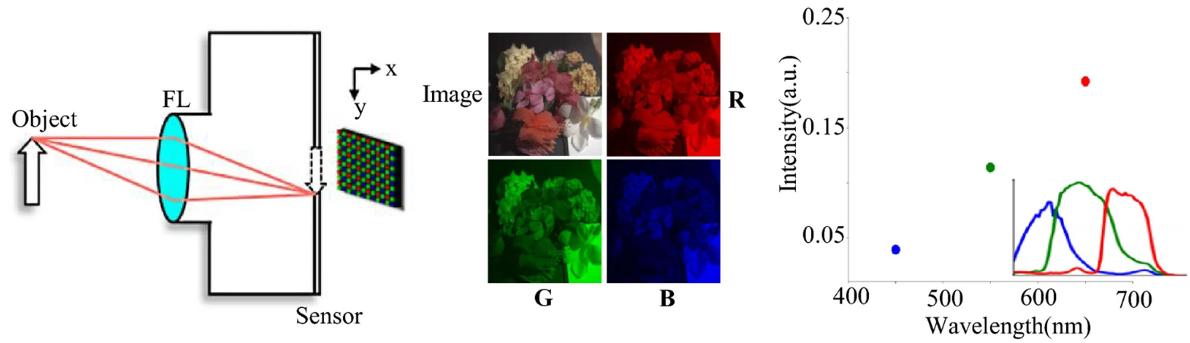

Figure 2. Schematic diagram of an RGB imaging, with each pixel is combined with three discrete colour values, which are integrated from wide R, G, B spectra (Jingang et al., 2022).

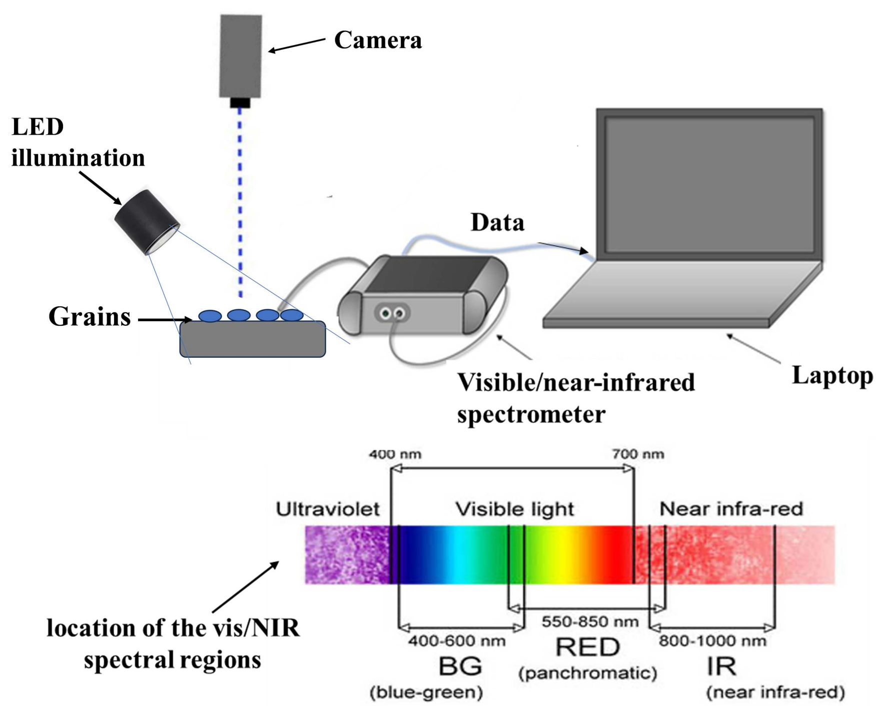

Figure 3. Schematic illustration of a VIS-NIR imaging system, showing the electromagnetic spectrum and highlighting the positions of the VIS and NIR spectral regions.

surface characteristics such as shape, colour, and size, while NIR spectroscopy measures properties like protein content, moisture levels, and oil content. Both techniques have been widely studied in relation to cereal grain storage (Shen et al., 2019). For instance, VIS imaging has been used to detect cracks in rice kernels (Wang et al., 2022), while NIR spectroscopy has been employed to measure components in wheat flour, such as starch and water absorption capacity (Zhang et al., 2022). These methods provide valuable information on overall quality parameters, helping decision-makers determine whether stored grains should remain in storage based on their market value (Feng et al., 2019).

VIS and NIR imaging serve as powerful tools for grain monitoring and applications. By combining the visible light spectrum with NIR, these techniques capture detailed information about grains' physical characteristics, including size, shape, moisture content, and colour (Jimoh et al., 2025). This data can be used to optimize harvest timing or identify potential storage issues like insect infestations or fungal growth. Additionally, the technology has found applications in agricultural research for crop yield prediction, the food processing industry for quality control, and the seed production industry for genetic selection. Wang et al. (2022) used 283 visible and NIR imaging to evaluate the quality of rice grains, finding that the technique accurately 284 predicted quality attributes like protein content and dough strength. Ramirez et al. (2019) applied 285 VIS and NIR imaging to predict protein and moisture content in grains, achieving R^2 values greater than 0.9. Furthermore, Visible-NIR imaging provides a reliable and efficient method of monitoring grain quality, offering numerous advantages over traditional inspection methods and making it an invaluable resource in modern agriculture.

4.3 Multispectral imaging

Multispectral Imaging (MSI) is an advanced technique for grain monitoring that uses multiple wavelengths of light to capture detailed images as depicted in Figure 4. These wavelengths can include visible spectrum (red, green, and blue), or non-visible spectrum, such as in the infrared or ultraviolet range. By analysing data across these wavelengths, it is possible to identify materials and their properties in the scene. This technology enhances grain quality assessment by detecting subtle characteristics like moisture content, protein levels, discoloration, and texture more accurately than traditional methods (Hussein et al., 2019). An additional advantage of MSI is its flexibility; it can be applied on-site or remotely, using drone or satellite imagery (Giraldo & Venturini, 2020). It is also highly effective for agricultural remote sensing, enabling quick assessments through comprehensive high-resolution datasets.

Several studies have demonstrated the effectiveness of MSI in grain applications. Gonzá et al. (2020) showed that MSI can remotely measure parameters such as size, shape, colour, and moisture content. Liu

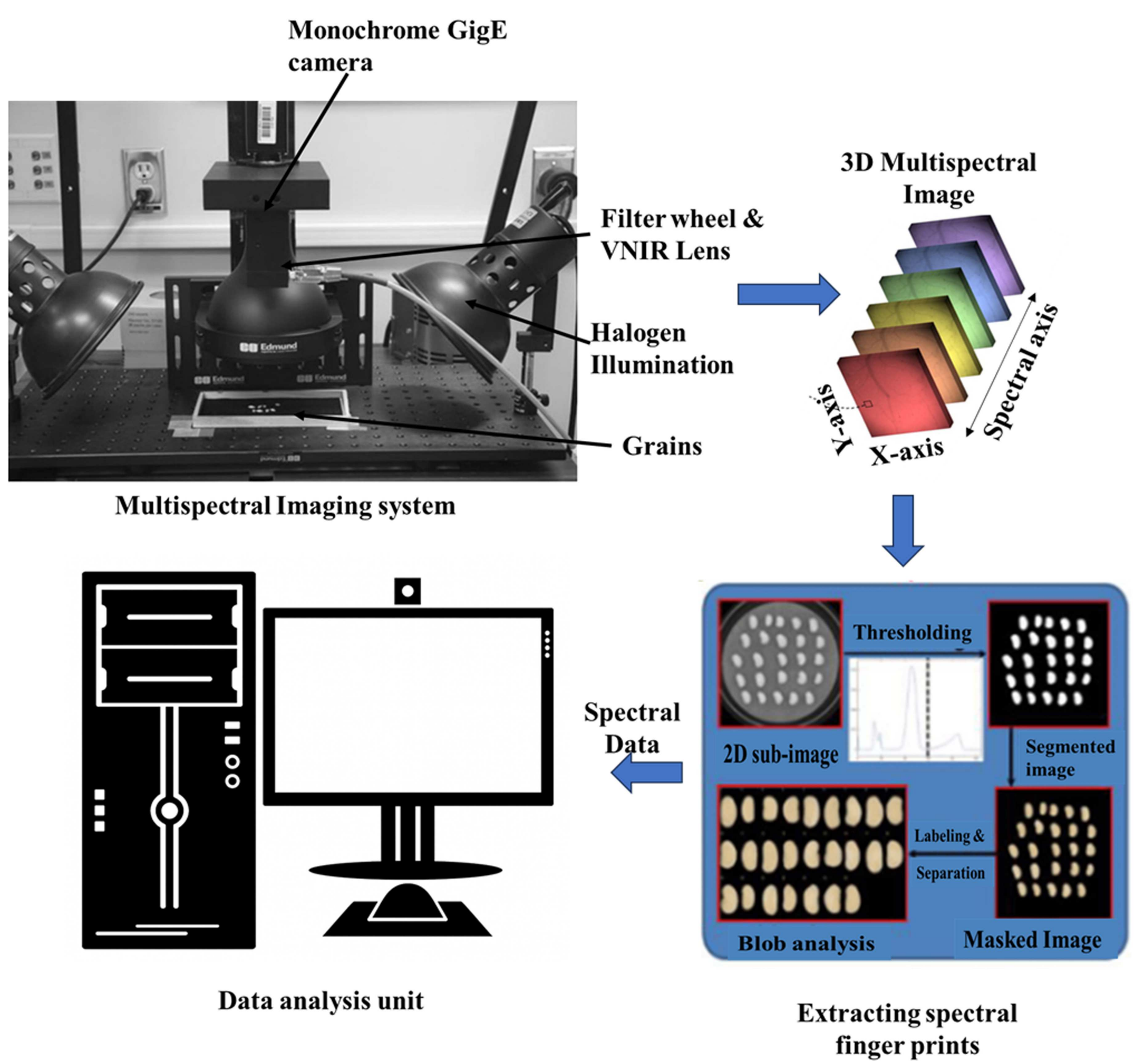

Figure 4. Schematic representation of the MSI system and image analysis for seed quality evaluation.

et al. (2014) successfully distinguished transgenic rice seeds from non-transgenic ones using chemometric analysis combined with a least squares support vector machine (LS-SVM), achieving 100% classification accuracy. MSI has also been used to identify maize defects, for example, Li et al. (2022) applied MSI with a genetic algorithm-back-propagation neural network (GA-BPNN) to detect zearalenone (ZEN) contamination in maize, reaching an accuracy of 93.33%. Sendin et al. (2018) used object-wise partial least squares discriminant analysis (PLS-DA), achieving classification accuracies ranging from 83% to 100%.

Different approaches to MSI, such as filters, prisms, and hyperspectral sensors, are tailored to specific applications, each offering distinct advantages and limitations depending on the imaging system's requirements (Alnaggar et al., 2023). For instance, Sun et al. (2009) detected barley scab using MSI and found that the LS-SVM model provided the highest prediction accuracy at 93.9%. Zhang et al. (2018) demonstrated the utility of MSI in monitoring the moisture content of stored rice, which is crucial for preventing pest infestations and diseases. Additionally, Xu et al. (2017) showed that MSI can enhance crop yields by improving the accuracy of pest control. By leveraging MSI, farmers can make more informed decisions, resulting in greater productivity and reduced labour.

4.4 Hyperspectral imaging

HSI is an advanced photoelectric, non-destructive testing that combines spectral and imaging data. HSI acquisition methods can be categorized into three types: point, line, and surface scanning. Point scanning captures the spectrum of one pixel at a time, making it inefficient (Lu et al., 2017). Line scanning is more common, simultaneously capturing the spectrum of all points along a scanning line. Surface scanning, however, stands out by acquiring a full spatial image at a single wavelength in one step (Li et al., 2022). HSI captures and analyses images across a wide range of electromagnetic wavelengths, typically covering visible and near-infrared spectra (Ravikant et al., 2017). While similar to MSI, HSI provides finer spectral resolution with more spectral bands. The rich spectral data obtained can be analysed using image-processing techniques to extract crucial features, provided that no valuable information is lost during processing. Reflectance, absorbance, or both spectra can be produced, facilitating chemometric analysis. Diffuse reflectance spectra are generated when near-infrared radiation penetrates deep into samples, while absorbance spectra result from radiation absorbed by the sample, enabling sample characterisation and concentration determination.

HSI generates a comprehensive dataset called a data cube, consisting of 50–300 images captured at various wavelengths with a spectral resolution of 1–10 nm. These images can be transformed into radiometric quantities like transmittance, absorbance, and reflectance, revealing chemical compositions and physical properties (Adebayo et al., 2016). A typical HSI system comprises a charge-coupled device (CCD) camera, detector, frame grabber, filter, illumination system (e.g. halogen lights), and a computer for processing the large datasets (Bachik et al., 2020), as illustrated in Figure 5.

HSI has proven effective in grain quality evaluation by identifying traits such as protein, starch, and moisture content. For instance, it has been employed to accurately predict the protein content, falling number, and sedimentation value of wheat (Jha et al., 2017). Similarly, Sun et al. (2021) demonstrated its utility in analysing barley seeds using discriminant models like k-nearest neighbours (KNN), SVM, and RF. Feature wavelength selection using the successive projections algorithm further improved prediction accuracy, achieving over 93% for wheat and maize quality assessments. HSI technology was also used to quantitatively predict the contents of sucrose, caffeine, and triglycerides in single coffee beans (Caporaso et al., 2018).

By capturing several small spectral bands across a broad range of wavelengths, HSI enables the identification of specific molecular and chemical compounds within grains. Femenias et al. (2022) used HSI to predict chemical compounds in rice, showing that it can accurately predict protein, moisture, and amylose contents with coefficients of determination (R^2) of 0.95, 0.92, and 0.89, respectively. In addition, HSI can distinguish between different types of rice, such as jasmine rice and basmati rice, based on their spectral characteristics. A study by Aulia et al. (2022), used HSI to predict the protein content of soyabeans, the spectral data acquired from the HSI 3D hypercube were synced to the chemical analysis reference values. The calibration model was built using partial least square regression (PLSR) techniques and verified using the remaining 30% of spectral data. The HSI methodology was shown to be a viable method for

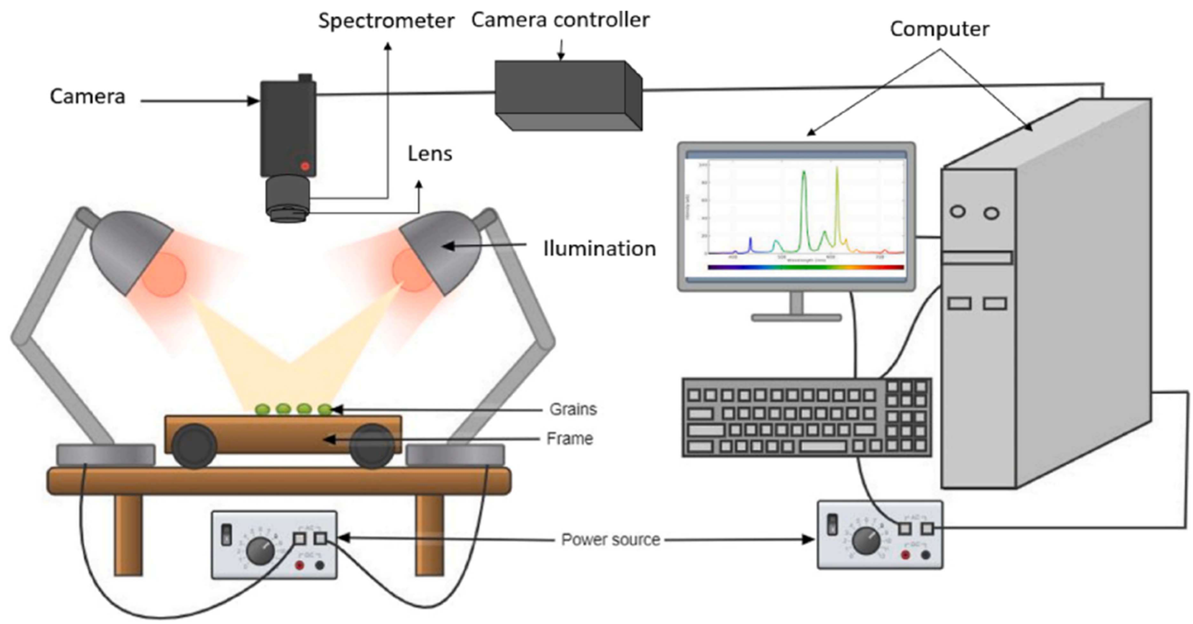

Figure 5. Setup for HSI system (Jimoh et al., 2023).

predicting protein content in soybean seeds, with an R^2 of 0.92 and an RMSE of 1.08%. Furthermore, the chemical pictures visualized the distribution of protein content for many soybean seeds, demonstrating the potential of the established approach for the application of a quick assessment of huge samples in the processing line.

One key application of HSI is detecting and identifying materials and substances based on their unique spectral signatures (Sun et al., 2023). For example, it can be used to identify the presence of certain chemicals, minerals, or biological materials in a sample, based on the absorption and reflection of light at different wavelengths (Ravikant et al., 2017). A study by Wang and Song (2023) used HSI for identifying the variety of sweet maize seeds. The experimental analysis results show that the deep learning model performed best with a classification accuracy of over 95% in the training and test sets.

Additionally, HSI can be used to detect contaminants such as mycotoxins, which are toxic compounds produced by certain fungi, which pose risks to human health and grain quality. The HSI technique can be used to monitor diseases and the level of infestation in grains. Praprotnik et al. (2023) used HSI to detect pest infestation in maize for 28 days. It was detected that pest infestation in maize has the highest overall accuracy on day 14 (84.7%) and the lowest on day 28 (67%). A study by Yipeng et al. (2022) used the 'Bag of texton' (BoSW) model to analyse the 3D HSI of rice panicles from more than 50 cultivars. The samples were collected in two different seasons from the same field under natural conditions to enable blast disease grading. The study used an HSI to capture images of 312 rice panicles at the yellow-ripe stage, which had different levels of blast infection (0, 1, 3, 5, 7, and 9). The images were collected in two batches and a spectrum prototype concept was proposed. The statistical distribution of the spectrum prototype was then used to grade the severity level of the rice blast, with 186 samples used for training and 126 for testing, combining the two batches. The results showed that the proposed method was able to grade rice panicle blasts with 81.41% accuracy for six-class grading and 96.40% accuracy for two-class grading in the validation datasets. The classification model was constructed using an SVM, and the BoSW method offered the best performance compared to the other baseline methods. Another study by Senthilkumar et al. (2016) used HSI to detect fungal disease in stored barley. A significant wavelength and histogram characteristics were identified and utilized as input for linear, quadratic, and Mahalanobis statistical classifiers. To distinguish between sterile and infected kernels, pairwise, two-class, and six-class classification models were created. The three classifiers distinguished sterile kernels with a classification accuracy of more than 94%, fungal-infected kernels with a classification accuracy of more than 80% during the earliest stages of fungal infection, and fungal-infected kernels with a classification accuracy of 100% after four weeks of storage.

4.5 Fluorescence imaging

FI is a valuable technique for analysing and characterising grains, particularly in plant and food sciences. It uses fluorescent dyes or labels to highlight specific components or structures within a sample, which are visualized using a microscope or imaging device. The method works on the principle that certain compounds emit light when excited by specific wavelengths. FI can detect various compounds, including proteins, carbohydrates, lipids, and pigments, making it effective for assessing grain quality traits such as protein content, starch content, and colour. Additionally, it can identify contaminants such as pesticide residues, which are crucial due to their potential health risks (Delwiche et al., 2019).

A key advantage of FI is its high sensitivity and resolution, enabling the detection of trace amounts of fluorescently labelled molecules in a sample. This makes it particularly useful for 409 identifying and quantifying grain components such as proteins, carbohydrates, and lipids. Su et al. (2019) used FI to monitor the translocation behaviour of beans, demonstrating its effectiveness as a rapid and reliable method for studying the real-time movement of signalling markers in crop systems. Similarly, Herritt et al. (2020) applied FI to assess the photochemical efficiency of sorghum. Their findings showed that the imaging system accurately measured photochemical efficiency, with a strong correlation ($r = 0.92$) to handheld fluorometer readings. Moreover, the system effectively tracked the decline in photochemical efficiency caused by herbicide treatment over a seven-day period.

FI is widely used in plant science to study the distribution and dynamics of grain components during development and maturation. For example, Zhang et al. (2019) demonstrated its ability to visualize starch granule distribution and accumulation in grain endosperm tissue. This helps identify differences in starch content and quality among plant species and varieties, which impacts food processing and nutritional value. FI has also been used to study plant defence mechanisms in grains. Jones et al. (2016) used it to map the distribution and accumulation of phytoalexins, compounds produced by plants in response to stress or infection. This insight aids in understanding plant stress responses and developing strategies to enhance crop resilience.

FI is widely used in food science to study the structural and functional properties of grains and grain-based products. For example, Rathnayake et al. (2018) used FI to visualize the microstructure of grains, providing insights into factors affecting grain quality and texture. Zhao et al. (2018) demonstrated its application in monitoring maize growth rates. A promising use of FI in food science is analysing gluten proteins in grains. These proteins affect dough elasticity but can trigger adverse reactions in individuals with coeliac disease or gluten sensitivity. Graziano et al. (2020) used FI to study the distribution and structure of gluten proteins in various grain varieties and evaluate how processing techniques modify gluten structure. However, FI has limitations. It often requires fluorescent labels or dyes that may alter sample properties and are not suitable for all applications. Additionally, FI is limited to detecting labelled molecules, which might not fully represent the sample. The technique can also be time-consuming and requires specialized equipment and expertise, posing challenges for some research groups.

4.6 Thermal imaging

Thermal Imaging (TI) is a non-invasive and non-destructive technique widely used in food and agricultural sciences for analysing and characterising grains. By capturing infrared radiation emitted from objects and translating it into thermal images, the TI system reveals variations in thermal properties such as heat absorption, emission, and conduction as depicted in Figure 6. These variations correspond to the physical and chemical characteristics of grains, making it possible to assess their quality and detect defects. For instance, rice grains with varying moisture content exhibit distinct thermal profiles, enabling precise evaluations of grain quality and identification of adulteration or contamination. One key application of the TI system in grain analysis is moisture content determination, a critical factor affecting storage, shelf life, and processing. By analysing temperature gradients, TI can accurately measure both surface and internal moisture distribution in grains, such as rice, and assess its equilibrium moisture content during drying or storage (Vadivambal & Jayas, 2011). Additionally, TI is effective in detecting adulteration by identifying differences in thermal profiles between authentic and contaminated grains. For example, melamine-contaminated rice shows distinct thermal behaviours during heating, which can be detected using advanced image analysis and ML algorithms (Ponnusamy et al., 2023).

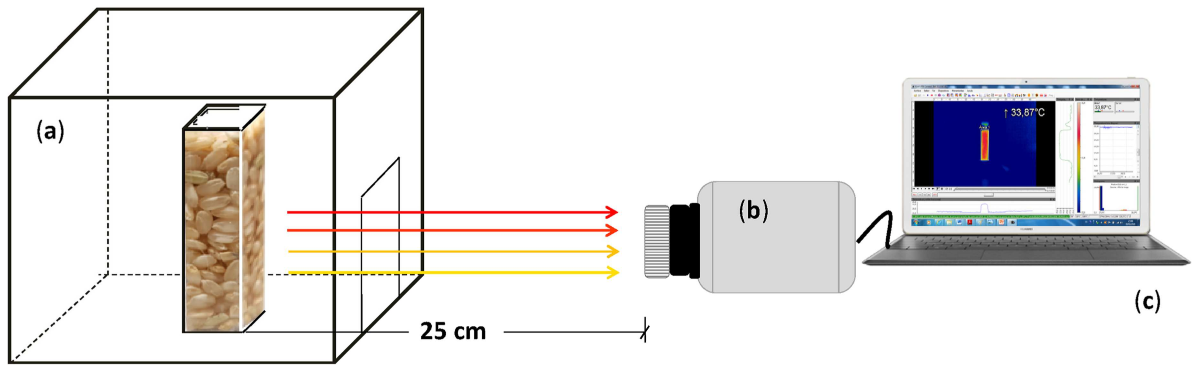

Figure 6. Setup for TI system (a) adiabatic chamber includes the cuvette containing the rice samples; (b) thermographic camera located at 25 cm; (c) computer (Estrada-Pérez et al., 2021).

TI also excels in detecting structural defects in grains, such as cracks and fissures, by leveraging variations in thermal conductivity and heat retention. These defects, often invisible to the naked eye, are clearly distinguishable in thermal images (Osornio-Rios et al., 2019). Furthermore, TI provides valuable insights into the thermal behaviour of starch and proteins in grains, enabling studies of functional properties such as starch crystallinity and the amylose-amylopectin ratio. The technology has also been employed to detect pest infestations in stored grains by identifying thermal anomalies caused by metabolic heat generated by insects, offering a non-destructive solution for early pest detection.

The advantages of TI include its portability, rapid imaging capabilities, and non-contact nature, making it ideal for on-site grain quality monitoring. It requires minimal sample preparation, offers real-time analysis, and can be integrated with advanced data analysis techniques like AI for enhanced accuracy and reliability (Estrada-Pérez et al., 2021). However, limitations such as sensitivity to external factors like ambient temperature and humidity, the high cost of equipment, and the need for skilled operators may restrict its widespread adoption in some settings. With ongoing advancements in imaging technology and data analytics, TI is expected to play a transformative role in grain quality assurance, supply chain management, and fraud detection. Its ability to provide reliable, cost-effective, and sustainable solutions makes it a valuable tool for addressing the growing demand for quality control in the food and agricultural industries.

4.7 X-ray imaging

X-ray imaging is a powerful tool for evaluating the internal quality of grains due to its ability to penetrate deep into materials and reveal hidden structures. X-rays, a type of electromagnetic radiation, possess high-energy wavelengths that allow them to interact with matter in a way that reveals internal damage such as cracks, fissures, and structural flaws within grains (Zhang, 2021). This capability is particularly beneficial for assessing the internal integrity of food grains, which is vital for determining their quality. X-rays can be divided into two types: hard X-rays and soft X-rays. Hard X-rays, which have shorter wavelengths (less than 1 nm), are known for their higher energy and penetration power, whereas soft X-rays, with longer wavelengths (1–10 nm), are less penetrating (Olakanmi et al., 2023).

In practical applications, X-ray systems commonly consist of a gas tube, or filament cathode, and an anode, which together generate X-rays that are emitted in all directions and pass through a glass window, as illustrated in Figure 7. The efficiency of X-ray production is influenced by the properties of the target material used in the anode, with certain materials enhancing the quantity and quality of the X-rays produced (Jimoh et al., 2023). X-ray imaging has been particularly useful in evaluating the structural quality of grains during and after various drying processes. For instance, Chatchavanthatri et al. (2021) used X-ray imaging to examine the internal microstructure of different rice types, such as brown and parboiled germinated rice, dried using various methods. They found that infrared drying significantly reduced fissures in the rice, resulting in a higher head rice yield, as revealed by X-ray imaging. Similarly, during the drying process, X-rays have been used to track the formation of fissures in rough rice kernels, with temperature and humidity levels shown to influence the extent of damage (Odek et al., 2020). Overall, X-ray imaging is

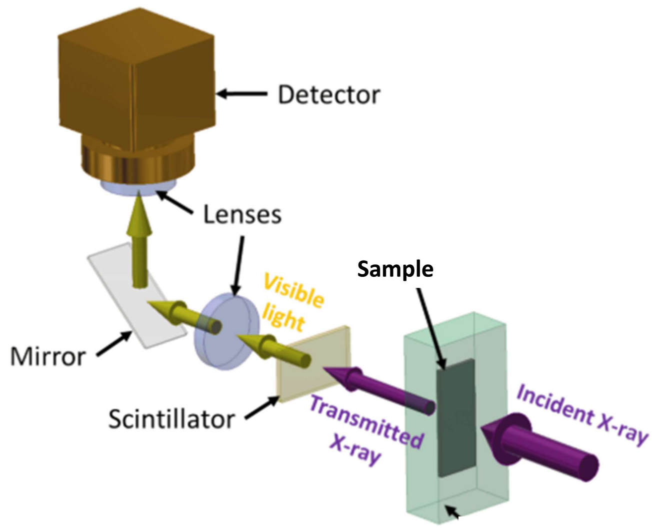

Figure 7. Setup for X-ray imaging system (Feng et al., 2022).

an essential tool for assessing the quality of grains, allowing for the detection of internal defects and offering valuable insights into the effects of different drying techniques on grain structure and quality.

4.8 UV imaging

Ultraviolet (UV) imaging is a powerful technique used in assessing the quality of grains, particularly in detecting various biochemical properties of plant tissues. The UV spectrum, ranging from 100 to 400 nm, plays a crucial role in the imaging process, as it can reveal structures and compounds that are otherwise not visible under visible light. UV radiation excites natural fluorophores within the grain tissues, causing them to emit fluorescence, which can then be captured in detailed images. These fluorophores, such as lignin and phenolic compounds, are key markers for understanding the structural and chemical composition of plant tissues (Corcel et al., 2016). In grain quality assessment, it is often employed to observe the integrity and structure of the cell walls, as plant cell walls contain compounds like lignin and hydroxycinnamic acids, which exhibit strong autofluorescence under UV light (Yoshioka et al., 2013). This fluorescence can be used to identify different layers of the grain, such as the aleurone layer, pericarp, and testa, by analysing multispectral images captured at different UV excitation wavelengths. These layers are of particular interest in grain quality analysis because their structure influences properties such as grain hardness, nutritional content, and resistance to damage during storage and processing.

UV fluorescence imaging has several advantages for grain quality evaluation. It can provide high-resolution images at the micrometric scale, enabling the detection of tissue dissociation, which is important when studying the quality and integrity of broken or fragmented grains. Furthermore, UV imaging can be used to track changes in the grain's internal structure, such as the formation of cracks, which can occur during various processes like drying or milling. For instance, Yoshioka et al. (2013) used UV fluorescence to observe the distribution of phenolic compounds in plant tissues, which could be linked to the grain's resistance to damage.

In practice, UV imaging systems typically use a combination of excitation and emission filters to capture a range of fluorescence signals. By employing different excitation wavelengths, the imaging system can obtain multispectral images that provide detailed information about the composition and structure of different grain tissues. These images can be analysed using advanced chemometric methods, such as PCA, to predict grain quality based on the autofluorescence profiles obtained from various tissues (Baldwin et al., 1997). This method has been used successfully to identify specific tissues within grain samples, such as the aleurone and pericarp, and to assess their quality in terms of nutrient content, structural integrity, and resistance to environmental stresses. UV imaging's ability to non-destructively visualize grain structures and biochemical properties makes it an invaluable tool in grain quality control, providing insight into both visible and hidden defects that might affect grain quality during storage, processing, and final consumption.

5 Artificial intelligence in grain quality evaluation

Advances in AI algorithms have significantly enhanced the ability to detect subtle differences between samples, making them ideal for large-scale production that require both efficiency and accuracy. In the food grain industry, maintaining high-quality standards is essential to meet market demands and ensure food security. However, traditional evaluation methods such as microbiological and chemical tests are expensive, time-consuming, and prone to human error. To overcome these challenges, there is a need for fast, precise, and non-destructive tools for grain quality inspection. Optical imaging integrated with AI has emerged as a popular solution for grain quality assessment. It enables rapid and cost-effective analysis of large quantities of grains using high-resolution images, which allow for accurate measurement of grain characteristics. These non-invasive techniques facilitate high-throughput analysis, making them exceptionally valuable for the agricultural sector (Ageh et al., 2024; Chen et al., 2020). A key component of AI empowers systems to learn from data and replicate human decision-making. This makes AI a powerful tool for modelling complex processes such as grain quality assessment. AI algorithms, including ANN, SVM, KNN, RF, and PCA, are widely applied in analysing optical images of grains for classification and regression tasks (Ayobami et al., 2024; Bhupendra et al., 2022; Rabanera et al., 2021; Zareef et al., 2021).

The integration of AI with big data and advanced information processing has transformed grain drying processes by effectively addressing dynamic and nonlinear challenges (Dasore et al., 2025). Image processing techniques, whether partial or comprehensive, are used to convert raw data into meaningful inputs for AI models. These models are trained to identify patterns and predict key variables such as moisture distribution, temperature uniformity, and overall grain quality (Bhupendra et al., 2022; Rabanera et al., 2021). Once trained, AI models can deliver accurate, real-time predictions and decisions, enabling efficient monitoring and quality assessment throughout the grain drying process (Zareef et al., 2021). For instance, Jin et al. (2021) employed backpropagation neural networks (BPNN) to model heat and mass transfer during grain drying and integrated the model with an intelligent control system to manage grain discharge rates and optimize drying parameters. Similarly, Jin et al. (2022) developed a real-time moisture analyser for paddy, combining microstrip sensors with AI algorithms such as SVMs and decision trees. Their RF model achieved 99% accuracy in moisture content prediction, with a root mean square error of 0.28. These innovations demonstrate how AI enhances grain drying processes and quality analysis, ultimately improving agricultural efficiency and food product standards.

6 Comparative analysis of imaging techniques

Table 2 presents a detailed comparative analysis of these imaging techniques, emphasising their distinct strengths, applications, and limitations. The selection of an appropriate imaging method depends on the specific grain quality attribute under evaluation whether it is surface defects, internal structure, moisture content, or contamination. While each technique offers particular advantages, they also come with challenges such as high costs, the need for specialized equipment, and limitations in resolution or analytical depth. By systematically examining these factors, the analysis provides a comprehensive understanding of the technologies and offers valuable insights into how they can be integrated to achieve more robust, precise, and efficient grain quality assessment.

7 Future perspectives

The future of optical imaging in grain quality evaluation is highly promising, driven by continuous advancements in technology and AI. As precision agriculture and food safety requirements increase, optical imaging is expected to play an even more pivotal role in providing fast, accurate, and non-destructive analysis of grain quality. Emerging technologies and innovative applications are shaping its evolution, enabling more robust and scalable solutions for the agricultural industry. One key area of growth is the integration of AI with advanced imaging techniques like HSI. These technologies enhance the ability to detect and classify grain attributes such as protein content, moisture levels, structural integrity, and contaminants. AI models can analyse large datasets to identify patterns and automate quality assessments,

Table 2. Comparative analysis of various imaging techniques for grain quality evaluation.

Modality	Principle	Image processing and data analysis	Applications	Advantages	Limitations	Reference
RGB imaging	Captures spatial information using three primary colour channels (red, green, and blue). Images are acquired under natural or controlled lighting, with settings adjusted for focus, resolution, and colour calibration. Data is stored in standard formats (e.g. JPG) for further analysis. Calibration with colour charts to ensure accuracy.	1. *Image acquisition*: capturing images under controlled or natural lighting with proper settings. 2. *Preprocessing:* enhancing image quality through noise reduction, resizing, and colour calibration. 3. *Feature extraction:* analysing colour properties, textures, and shape characteristics. 4. *Segmentation:* identifying and isolating regions of interest. 5. *Data analysis*: applying statistical and computational methods to extract meaningful insights. 6. *Validation:* comparing extracted features with reference measurements.	Disease scoring; Nutritional composition prediction; Assessing plant growth and water status; Measuring seed vigour for cultivar selection; Non-destructive grain quality assessment for trade; Estimating chlorophyll, carotenoid, and nitrogen concentrations in plants	Non-invasive and rapid analysis; cost-effective compared to spectral imaging; easy to operate and widely accessible	Limited to external features; cannot assess internal structures; calibration challenges due to varying illumination and camera optics; a single viewpoint may not represent 3D traits like volume or surface area.	Fernandez-Gallego et al. (2019)
VIS and NIR imaging	Captures spatial and spectral information in the visible (400–700 nm) and near-infrared (700–2500 nm) regions. Measures light absorption, reflection, and transmission to analyse material properties.	1. *Image acquisition*: capture spectral data using appropriate light sources and detectors. 2. *Preprocessing*: noise reduction, illumination correction, and normalisation. 3. *Feature extraction*: extract spectral reflectance, absorption, and texture features. 4. *Data analysis & classification:* use statistical or ML models to classify or predict material properties. 5. *Validation & interpretation:* evaluate model performance and interpret results for decision-making.	Moisture content determination, Grain colour classification, Identification of damaged grains, Detection of insect infestation, Fungal contamination, and Mycotoxin detection.	Non-destructive, non-invasive, rapid analysis. Can assess both physical and chemical attributes. Wide applicability in grain quality evaluation.	Limited spectral resolution compared to HSI. Sensitive to environmental factors like lighting. Requires careful calibration for consistent results.	Ramirez et al. (2019)
MSI	Captures spatial and spectral data across a limited number of discrete wavelengths. Integrates optical imaging and spectroscopy to focus on specific spectral bands relevant for targeted analyses.	1. *Image acquisition & calibration:* capture images across selected spectral bands; perform radiometric, geometric, and white reference calibration. 2. *Preprocessing:* apply noise reduction (filtering), illumination correction, and background segmentation. 3. *Feature extraction:* extract spectral signatures, texture, and morphological properties. 4. *Spectral data processing & classification*: analyse spectral responses using statistical, ML, or clustering techniques (PCA, CDA, k-means). 5. *Validation & decision-making*: compare results with reference datasets and optimize classification accuracy.	Varietal purity testing in grains; Detection of insect damage and fungal infection; Grain contaminant identification; Classification of seed traits during conservation; Quality grading and seed health assessment; Evaluation of germination capacity, vigour, and surface structure; Determination of seed composition and chemical properties	Operates effectively in various environments; versatile for multiple applications; provides balanced spatial and spectral resolution; non-destructive; cost-effective compared to HSI	Limited spectral detail compared to HSI; Higher risk of misclassification for materials with similar spectral features; Requires complex data processing; Resolution suitable only for specified areas or timeframes	Shahin et al. (2012)
HSI	Captures both spatial and spectral data across a wide range of wavelengths (UV to SWIR). It integrates digital imaging, radiometry, and spectrometry to provide a detailed analysis of physical	1. *Image acquisition & calibration:* capture HSI cubes; perform dark current correction, radiometric calibration, and geometric alignment. 2. *Preprocessing:* apply noise reduction (e.g. Savitzky-Golay smoothing), spectral normalisation, and background removal to enhance spectral signal clarity.	Colour classification of grains, Identification of healthy vs. insect-damaged kernels, Prediction of chemical composition; Detection of fungal contamination and mycotoxins; Detection of	Non-destructive, non-contact, non-invasive. Provides chemical imaging for detailed analysis. Saves time compared to traditional methods.	Expensive, complex data processing, and large storage requirements. Signal quality is affected by environmental factors. Difficult identification of items	ElMasry and Sun, 2010; Ndubisi et al. (2022); Sharma et al. (2024)

(*Continued*)

Table 2. (*Continued*)

Modality	Principle	Image processing and data analysis	Applications	Advantages	Limitations	Reference
	and chemical properties, by creating a hypercube with two spatial and one spectral dimension	3. *Feature extraction*: extract full spectral signatures, spectral indices, and spatial features; apply band selection or dimensionality reduction (PCA, LDA). 4. *Spectral analysis & classification:* utilize ML and statistical methods to classify grain quality, detect contaminants, and predict chemical composition. 5. *Validation & Interpretation:* cross-validate models, compare spectral responses with reference datasets, and optimize algorithms for accuracy improvement.	insect infestation; Assessment of grain viability and quality during storage	Simultaneous spectral and spatial data.	with similar spectral features.	
FI	It works by exciting specific molecules in a product with light, which then re-emits light at a longer wavelength. The emitted light is analysed to detect specific fluorescence signatures, which can be used to assess the quality and characteristics of agricultural products. This technique exploits the natural fluorescence of certain molecules or uses artificial fluorophores.	1. *Image acquisition & calibration*: capture FI under controlled UV or VIS excitation, calibrate with reference standards to ensure consistency. 2. *Preprocessing*: apply background subtraction to remove ambient light interference, perform noise reduction (Gaussian smoothing, median filtering), and correct intensity variations. 3. *Segmentation & feature extraction*: use intensity thresholding, morphological operations, or ML-based segmentation to isolate fluorescence regions. Extract fluorescence intensity, spectral signatures, and spatial distribution features. 4. *Data processing & classification*: analyse fluorescence intensity profiles using statistical/ML models, classify samples based on fluorescence signatures, and apply chemometric techniques for quantitative analysis. 5. *Validation & interpretation*: compare FI with ground truth data, enhance contrast using pseudo-colour mapping, and correlate fluorescence intensity with quality parameters.	Grain quality prediction through chlorophyll-related fluorescence indices; rice variety classification based on fluorescence signals; disease detection by analysing spatial variation in chlorophyll fluorescence; detection of bran residue on milled rice;	Non-destructive and rapid; high contrast for detecting surface defects or internal characteristics; simple and cost-effective compared to HIS; sensitive to specific biochemical changes	Requires careful optimisation of lighting and camera settings; limited to the detection of fluorescence responsive compounds; sensitivity can be affected by external factors like lighting conditions or sample heterogeneity.	Momin et al. (2023)
TI	It detects infrared radiation emitted by an object and converts it into a visible temperature image.	1. *Image acquisition & calibration*: acquire TI under controlled conditions; calibrate temperature ranges with references. 2. *Preprocessing*: preprocessing enhances contrast by converting RGB to HSV and applying red colour recognition. 3. *Segmentation & feature extraction*: apply hue-based thresholding to isolate hot/cold spots, convert to grayscale for analysis, reduce noise with median filtering, generate binary ROIs, refine boundaries with morphological operations, and extract thermal patterns and spatial features. 4. *Data processing & classification*: calculate feature parameters (e.g. ratio of grey value ranges, pixel intensity ratios); classify images into healthy/	Detect infestation by identifying temperature differences caused by insects; evaluate seed quality (viability, germination, damage, impurities); identify bruises and quality issues in food products; monitor processing operations, ovens, and refrigerators.	Non-destructive and contactless evaluation; can detect hidden issues not visible on the surface; quick and efficient; portable and adaptable for field use.	Sensitive to environmental factors (ambient temperature); limited ability to measure deeper structures or internal changes; requires calibration and specialized equipment; may struggle with objects having similar temperature profiles.	Estrada-Pérez et al., 2021

Table 2. (*Continued*)

Modality	Principle	Image processing and data analysis	Applications	Advantages	Limitations	Reference
		diseased categories using defined thresholds and statistical models. 5. *Validation & interpretation*: compare output with ground truth (visual inspection or destructive sampling); interpret results for actionable insights (e.g. infestation presence, quality grading).				
X-ray imaging	X-rays are electromagnetic radiation that interacts with matter, causing attenuation, which is used to create images.	1. *Image acquisition & calibration*: capture X-ray images under controlled exposure and calibrate with reference phantoms to correct distortions. 2. *Preprocessing*: reduce noise (Gaussian filtering, wavelet denoising) and apply flat-field correction for detector variations. 3. *Segmentation & feature extraction*: use edge detection (Sobel, Canny) or thresholding to isolate key regions. Extract density, texture, and structural features. 4. *Data processing & classification*: analyse grayscale intensity profiles with statistical/ML models, refining defect detection using adaptive thresholding and morphological operations. 5. *Validation & interpretation*: compare with ground truth data, enhancing visualisation with contrast adjustment and false-colour mapping.	Internal quality evaluation of agricultural products including grains, fruits, and vegetables); detection of structural features	Non-destructive evaluation; high penetration power to reveal internal structures; rapid imaging (3–5 seconds)	Potential ionising radiation risk to humans; requires proper shielding to ensure safety; limited depth penetration	Kotwaliwale et al. (2014)
UVI	UVI involves the use of UV light (typically in the range of 200–400 nm) to excite certain compounds in grains, causing them to emit fluorescence or reflect light in a specific way. This fluorescence or reflection is captured to reveal hidden defects, infestations, or contamination in grains that are not visible under normal light	1. *Image acquisition & calibration*: capture UV images under controlled illumination with proper filtering and sensitivity adjustments. Perform geometric and radiometric calibration 2. *Preprocessing:* reduce noise (dark current subtraction, flat field correction), enhance contrast (histogram equalisation, adaptive filtering), and normalize intensity 3. *Segmentation & feature extraction:* isolate key regions of interest using thresholding or clustering methods. Extract fluorescence intensity, texture, and morphological features relevant to defect detection 4. *Data processing & classification:* analyse UV reflectance with statistical/ML models; apply PCA for dimensionality reduction 5. *Validation & interpretation:* compare with reference standards, enhance visualisation using false-colour mapping or intensity scaling	Detecting infestations; identifying contaminants or foreign materials; evaluating seed viability; monitoring germination and fungal presence	Non-destructive, can be done without direct contact; sensitive to specific defects not visible under normal light; can be used to detect contaminants and quality issues early	Limited penetration depth, surface-only evaluation; requires specialized equipment and setup; may not be effective for all types of grain defects	Corcel et al. (2016)

reducing labour and improving accuracy. Combining optical imaging with AI is expected to revolutionize grain quality evaluation, making it faster, more reliable, and cost-effective.

The development of portable imaging devices presents another exciting prospect. Equipped with cameras and spectral sensors, these devices can perform on-site inspections at farms, grain elevators, or storage facilities. Their portability allows for quick and convenient grain quality assessments without requiring samples to be transported to laboratories. As these devices become more accessible and affordable, they will empower farmers and food processors to make informed decisions in real time. Remote sensing and drone technology are also expected to significantly expand optical imaging applications. Drones equipped with hyperspectral sensors can capture high-resolution images and spectral data of crops directly in the field (Seo et al., 2023). This technology can analyse grain quality metrics such as protein and moisture content, offering valuable insights into crop health, yield potential, and grain quality even before harvest. These advancements can save time and labour while ensuring better monitoring and management of grain production at scale.

Despite its potential, optical imaging faces challenges, including sensitivity to environmental factors like light and temperature, high costs of advanced systems, and the need for large, labelled datasets to train AI models. Researchers are addressing these limitations through innovations such as synthetic data generation, improved system designs, and cost reductions in imaging technologies. To ensure that small-scale farmers benefit from these advancements, future research and industry efforts should focus on making imaging devices more affordable, user-friendly, and robust under diverse field conditions. Simplified interfaces, mobile-based applications, and training programs can help farmers adopt these technologies without requiring specialized technical expertise. Additionally, integrating optical imaging into existing grain evaluation systems such as local cooperatives, grain elevators, or extension services can facilitate shared access and support collective quality assessment. Partnerships between technology providers, agricultural organisations, and policymakers will be crucial for scaling deployment and ensuring equitable access.

Going forward, integrating optical imaging with emerging technologies will open new frontiers. For example, combining imaging systems with IoT-enabled devices could provide real-time data monitoring across the entire supply chain, while advances in computational imaging may further enhance resolution and processing speeds. These innovations will make grain quality evaluation more precise, scalable, and adaptable to diverse conditions. As technology continues to advance, optical imaging will become an indispensable tool in grain quality evaluation. Its ability to provide high-throughput, accurate, and actionable insights will support sustainable agricultural practices, improve food safety, and help meet the growing global demand for high-quality grain products.

8 Conclusion

Optical imaging techniques have revolutionized food grain quality evaluation by providing rapid, non-destructive, and highly detailed analysis of both physical and chemical grain attributes. This review demonstrates that technologies such as HSI, MSI, FI, TI, X-rays and UV imaging each offer unique advantages for assessing grain composition, detecting defects, and monitoring contamination. The integration of artificial intelligence with these imaging modalities further enhances accuracy, efficiency, and scalability, enabling high-throughput and automated grain quality assessment.

Despite these advancements, several research gaps remain. Current challenges include the high cost and complexity of advanced imaging systems, sensitivity to environmental factors, and the need for robust, generalized calibration models. There is also a pressing need for large, annotated datasets to train AI models, as well as portable, user-friendly devices for real-time field applications. Future research should focus on developing cost-effective, scalable imaging solutions, improving model robustness under variable conditions, and exploring the potential of IoT and remote sensing technologies for continuous, supply-chain-wide monitoring.

In summary, while optical imaging has made significant strides in grain quality evaluation, addressing these challenges will unlock its full potential and support the transition toward more sustainable, efficient, and resilient agricultural systems. Continued innovation in this field will not only enhance food safety and quality but also contribute to global efforts in achieving food security and sustainable development.

Author contributions

The study was conceptualized by Ageh Opeyemi and Norhashila Hashim. Ageh Opeyemi drafted the original manuscript. Norhashila Hashim and Abhishek Dasore revised and edited the manuscript. Norhashila Hashim acquired the funding for the study. Rosnah Shamsudin, Hasfalina Che Man, Mahirah Jahari and Daniel I. Onwude supervised and provided critical discussion and contribution to the manuscript revision.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The authors acknowledge the financial support of the Ministry of Higher Education, Malaysia, through the Transdisciplinary Research Grant Scheme Project (TRGS/1/2020/UPM/02/7).

ORCID

Norhashila Hashim 0000-0002-9063-5960
Rosnah Shamsudin 0000-0003-4849-9675

Data availability statement

The available data that are related to this study were included in the article

References

Abu Bakar, M. N., Abdullah, A. H., Rahim, N. A., Yazid, H., Misman, S. N., & Masnan, M. J. (2018). Rice leaf blast disease detection using multi-level colour image thresholding. *Journal of Telecommunication, Electronic and Computer Engineering*, *10*(1), 1–6.

Adebayo, S. E., Hashim, N., Abdan, K., & Hanafi, M. (2016). Application and potential of backscattering imaging techniques in agricultural and food processing – A review. *Journal of Food Engineering*, *169*, 155–164. https://doi.org/10.1016/j.jfoodeng.2015.08.006

Ageh, O. M., Dasore, A., Hashim, N., Shamsudin, R., Che Man, H., & Mohd Ali, M. (2024). Quality monitoring of glutinous rice processing from drying to extended storage using hyperspectral imaging. *Computers and Electronics in Agriculture*, *225*, 109348. https://doi.org/10.1016/j.compag.2024.109348

Alnaggar, Y. A., Sebaq, A., Amer, K., Naeem, E., & Elhelw, M. (2023). Rice plant disease detection and diagnosis using deep convolutional neural networks and multispectral imaging. In P. Fournier-Viger, A. Hassan, & L. Bellatreche (Eds.), *Lecture Notes in Computer Science* (Vol. *13761*, pp. 2022–2025). Springer, Cham. https://doi.org/10.1007/978-3-031-21595-7_2

Aulia, R., Kim, Y., Amanah, H. Z., Andi, A. M. A., Kim, H., Kim, H., Lee, W. H., Kim, K. H., Baek, J. H., & Cho, B. K. (2022). Non-destructive prediction of protein contents of soybean seeds using near-infrared hyperspectral imaging. *Infrared Physics Technology*, *127*, 104365. https://doi.org/10.1016/j.infrared.2022.104365

Ayobami, K. J., Hashim, N., Shamsudin, R., Che Man, H., & Jahari, M. (2024). Optimization of computational intelligence approach for the prediction of glutinous rice dehydration. *Journal of the Science of Food and Agriculture*, *104*, 6208–6220. https://doi.org/10.1002/jsfa.13445

Aznan, A., Gonzalez Viejo, C., Pang, A., & Fuentes, S. (2021). Computer vision and machine learning analysis of commercial rice grains: A potential digital approach for consumer perception studies. *Sensors*, *21*(19), 6354. https://doi.org/10.3390/s21196354

Bachik, N. A., Hashim, N., Wayayok, A., Man, H. C., & Ali, M. M. (2020). Optical imaging techniques for rice diseases detection: A review. *Journal of Agricultural and Food Engineering*, *1*(2020), 0001. http://doi.org/10.37865/jafe.2020.0001

Baldwin, P. M., Bertrand, D., Novales, B., Bouchet, B., Collobert, G., & Gallant, D. J. (1997). Chemometric labeling of cereal tissues in multichannel fluorescence microscopy images using discriminant analysis. *Analytical Chemistry*, *69*(21), 4339–4348. https://doi.org/10.1021/ac970145x

Bao, Y., & Li, J. (2020). Automated quality control system based on machine vision technology for food industry: A review study. *Scientific Reports*, *10*(1), 1–13. https://doi.org/10.1038/s41598-020-76236-9

Berger, M., Yang, Q., & Maier, A. (2018). X-ray Imaging. In Maier A., Steidl S., & Christlein V., et al. (Eds.), *Medical imaging systems: An introductory guide* (chapter 7 ed.). Springer. https://www.ncbi.nlm.nih.gov/books/NBK546155/https://doi.org/10.1007/978-3-319-96520-8_7

Bhupendra, Moses, K., Miglani, A., & Kumar Kankar, P. (2022). Deep CNN-based damage classification of milled rice grains using a high-magnification image dataset. *Computers and Electronics in Agriculture*, *195*, 106811. https://doi.org/10.1016/j.compag.2022.106811

Caporaso, N., Whitworth, M. B., Grebby, S., & Fisk, I. D. (2018). Non-destructive analysis of sucrose, caffeine and trigonelline on single green coffee beans by hyperspectral imaging. *Food Research International*, *106*, 193–203. https://doi.org/10.1016/j.foodres.2017.12.031

Chatchavanthatri, N., Junyusen, T., Arjharn, W., Treeamnuk, T., Junyusen, P., & Pakawanit, P. (2021). Effects of parboiling and infrared radiation drying on the quality of germinated brown rice. *Journal of Food Processing and Preservation*, *45*, 1–13. https://doi.org/10.1111/jfpp.15892

Chen, J., Zhang, M., Xu, B., Sun, J., & Mujumdar, A. S. (2020). Artificial intelligence-assisted technologies for controlling the drying of fruits and vegetables using physical fields: A review. *Trends in Food Science Technology*, *105*, 251–260. https://doi.org/10.1016/j.tifs.2020.08.015

Choudhury, A. K. R. (2014). Using instruments to quantify colour. In A. K. R. Choudhury (Ed.), *Principles of colour and appearance measurement* (pp. 270–317). Woodhead Publishing. ISBN 9780857092298. https://doi.org/10.1533/9780857099242.270

Corcel, M., Devaux, M. -F., Guillon, F., & Barron, C. (2016). Comparison of UV and visible autofluorescence of wheat grain tissues in macroscopic images of cross-sections and particles. *Computers and Electronics in Agriculture*, *127*, 281–288. https://doi.org/10.1016/j.compag.2016.06.016

Dasore, A., Hashim, N., Shamsudin, R., Man, H. C., Ali, M. M., & Ageh, O. M. (2025). Optimization of machine learning models for predicting glutinous rice quality stored under various conditions. *Journal of Stored Products Research*, *111*, 102550. https://doi.org/10.1016/j.jspr.2025.102550

Delwiche, S. R., Stommel, J. R., Kim, M. S., Vinyard, B. T., & Esquerre, C. (2019). Hyperspectral fluorescence imaging for shelf life evaluation of fresh-cut Bell and Jalapeno Pepper. *Scientia Horticulturae*, *246*, 749–758. https://doi.org/10.1016/j.scienta.2018.11.061

ElMasry, G., & Sun, D. -W. (2010). Principles of hyperspectral imaging technology. In D.-W. Sun (Ed.), *Hyperspectral imaging for food quality analysis and control*. (pp. 3–43). Academic Press. https://doi.org/10.1016/B978-0-12-374753-2.10001-2.

Estrada-Pérez, L. V., Pradana-López, S., Pérez-Calabuig, A. M., Mena, M. L., Cancilla, J. C., & Torrecilla, J. S. (2021). Thermal imaging of rice grains and flours to design convolutional systems to ensure quality and safety. *Food Control*, *121*, 107572. https://doi.org/10.1016/j.foodcont.2020.107572

Femenias, A., Gatius, F., Ramos, A. J., Teixido-Orries, I., & Marín, S. (2022). Hyperspectral imaging for the classification of individual cereal kernels according to fungal and mycotoxins contamination: A review. *Food Research International*, *155*, 111102. https://doi.org/10.1016/j.foodres.2022.111102

Feng, S., Liotti, E., & Grant, P. S. (2022). X-ray imaging of alloy solidification: Crystal formation, growth, instability, and defects. *Materials*, *15*(4), 1319. https://doi.org/10.3390/ma15041319

Feng, X., Chen, H., Chen, Y., Zhang, C., Liu, X., Weng, H., Xiao, S., Nie, P., & He, Y. (2019). Rapid detection of cadmium and its distribution in Miscanthus sacchariflorus based on visible and near-infrared hyperspectral imaging. *Science of the Total Environment*, *659*, 1021–1031. https://doi.org/10.1016/j.scitotenv.2018.12.045

Fernandez-Gallego, J. A., Kefauver, S. C., Vatter, T., Aparicio Gutiérrez, N., Nieto-Taladriz, M. T., & Araus, J. L. (2019). Low-cost assessment of grain yield in durum wheat using RGB images. *European Journal of Agronomy*, *105*, 146–156. https://doi.org/10.1016/j.eja.2019.02.007

Gan, H., Li, S., Ou, M., Yang, X., Huang, B., Liu, K., & Xue, Y. (2021). Fast and accurate detection of lactating sow nursing behavior with CNN-based optical flow and features. *Computers and Electronics in Agriculture*, *189*, 106384. https://doi.org/10.1016/j.compag.2021.106384

Ge, Y., Bai, G., Stoerger, V., & Schnable, J. C. (2016). Temporal dynamics of maize plant growth, water use, and leaf water content using automated high throughput RGB and hyperspectral imaging. *Computers and Electronics in Agriculture*, *127*, 625–632. https://doi.org/10.1016/j.compag.2016.07.028

Ghyar, B. S., & Birajdar, G. K. (2017). Computer vision based approach to detect rice leaf diseases using texture and color descriptors. 2017 International Conference on Inventive Computing and Informatics (ICICI), Coimbatore, India (pp. 1074–1078). https://doi.org/10.1109/ICICI.2017.8365305

Giraldo, S., & Venturini, O. (2020). Application of multitemporal UAV imagery for crop monitoring in northern Argentina using spectroscopy and image analysis techniques. *Remote Sensing*, *12*(10), 1693. https://doi.org/10.3390/rs12101699

González-Dugo, V., López, J. -A., & Sánchez, M. -J. (2020). Application of multispectral imaging techniques on grain products: A review study. *Food Engineering Reviews*, *12*(1), 1–17. https://doi.org/10/1007/s12393-019-09249-2

Graziano, S., Marmiroli, N., Visioli, G., & Gullì, M. (2020). Proteins and metabolites as indicators of flours quality and nutritional properties of two durum wheat varieties grown in different italian locations. *Foods*, *9*(3), 315. https://doi.org/10.3390/9030315

Guo, Y., Fu, Y. H., Chen, S., Bryant, C. R., Li, X., Senthilnath, J., Sun, H., Wang, S., Wu, Z., & de Beurs, K. M. (2021). Integrating spectral and textural information for identifying the tasseling date of summer maize using UAV based RGB images. *International Journal of Applied Earth Observation and Geoinformation*, *102*, 102435. https://doi.org/10.1016/j.jag.2021.102435

Herritt, M. T., Pauli, D., Mockler, T. C., & Thompson, A. L. (2020). Chlorophyll fluorescence imaging captures photochemical efficiency of grain sorghum (Sorghum bicolor) in a field setting. *Plant Methods*, *16*(1), 109. https://doi.org/10.1186/s13007-020-00650-0

Hussein, M., Khallaf, A., & El-Sayed, E. (2019). Assessment Of Grain Quality Parameters Using Hyperspectral Imaging Technique For Wheat Varieties Classification. *International Journal of Food Science Technology*, *54*(7), 1713–1720. https://doi.org/10.1111/ijfs.13518

Ireri, D., Belal, E., Okinda, C., Makange, N., & Ji, C. (2019). A computer vision system for defect discrimination and grading in tomatoes using machine learning and image processing. *Artificial Intelligence in Agriculture*, *2*, 28–37. https://doi.org/10.1016/j.aiia.2019.06.001

Jha, P., Singh, M., & Singh, V. (2017). Hyperspectral imaging: A review. *Applied Spectroscopy Reviews*, *51*(5), 479–494.

Jimoh, K. A., Hashim, N., Shamsudin, R., Che Man, H., & Jahari, M. (2023). Recent advances of optical imaging in the drying process of grains – A review. *Journal of Stored Products Research*, *103*, 102145. https://doi.org/10.1016/j.jspr.2023.102145

Jimoh, K. A., Hashim, N., Shamsudin, R., Man, H. C., & Jahari, M. (2025). Development of near-infrared hyperspectral-based smart interface for glutinous rice quality detection. Food control, *174*, 111252. https://doi.org/10.1016/j.foodcont.2025.111252

Jin, L., Qiu, S., & Wei, Z. (2022). Real-time measurement of moisture content of paddy rice based on a microstrip microwave sensor assisted by machine learning strategies. *Chemosensors*, *10*(10), 376. https://doi.org/10.3390/chemosensors10100376

Jin, Y., Wong, K. W., Yang, D., Zhang, Z., Wu, W., & Yin, J. (2021). A neural network model used in continuous grain dryer control system. *Drying Technology*, *40*, 1–22. https://doi.org/10.1080/07373937.2021.1891930

Jingang, Z., Su, R., Fu, Q., Zhang, J., Ren, W., Heide, F., & Nie, Y. (2022). A survey on computational spectral reconstruction methods from RGB to hyperspectral imaging. *Scientific Reports*, *12*, 11905. https://doi.org/10.1038/s41598-022-16223-1

Jones, K., Kim, D. W., Park, J. S., & Khang, C. H. (2016). Live-cell fluorescence imaging to investigate the dynamics of plant cell death during infection by the rice blast fungus Magnaporthe oryzae. *BMC Plant Biology*, *16*, 69. https://doi.org/10.1186/s12870-016-0756. PMID: 27000073; PMCID: PMC4802709.

Kotwaliwale, N., Singh, K., Kalne, A., Jha, S. N., Seth, N., & Kar, A. (2014). X-ray imaging methods for internal quality evaluation of agricultural produce. *Journal of Food Science and Technology*, *51*(1), 1–15. https://doi.org/10.1007/s13197-011-0485-y

Le, T. D. Q., Alvarado, C., Girousse, C., Legland, D., & Chateigner-Boutin, A. -L. (2019). Use of X-ray micro computed tomography imaging to analyze the morphology of wheat grain through its development. *Plant Methods*, *15*, 84. https://doi.org/10.1186/s13007-019-0468-y

Li, C., Hu, Q., Liang, Y., Wei, Y., & Wang, J. (2022, June 6). Physicochemical properties and application in film preparation of prolamin from distiller's grains. *International Journal of Food Science Technology*, *57*(8), 5206–5215. https://doi.org/10.1111/ijfs.15831

Li, L., Chen, S., Deng, M., & Gao, Z. (2022). Optical techniques in non-destructive detection of wheat quality: A review. *Grain Oil Science and Technology*, *5*(1), 44–57. https://doi.org/10.1016/j.gaost.2021.12.001

Lin, L., Jiang, P., Bao, Z., Pang, W., Ding, S., Yin, M. J., Li, P., & Gu, B. (2021). Fundamentals of optical imaging. Advances in Experimental Medicine and Biology, 3233, 1–22. https://doi.org/10.1007/978-981-15-7627-0_1

Liu, C., Liu, W., Lu, X., Chen, W., Yang, J., & Zheng, L. (2014). Nondestructive determination of transgenic Bacillus thuringiensis rice seeds (Oryza sativa L.) using multispectral imaging and chemometric methods. *Food Chemistry*, *153*, 87–93. https://doi.org/10.1016/j.foodchem.2013.11.166

Liu, S., Liu, X., Liu, M., Wu, L., Ding, C., & Huang, Z. (2017). Extraction of rice phenological differences under heavy metal stress using EVI time-series from HJ-1A/B data. *Sensors*, *17*(6), 1243. https://doi.org/10.3390/s17

Liu, W., Deng, H., Shi, Y., Liu, C., & Zheng, L. (2022). Application of multispectral imaging combined with machine learning methods for rapid and non-destructive detection of zearalenone (ZEN) in maize. *Measurement*, *203*, 111944. https://doi.org/10.1016/j.measurement.2022.111944

Liu, X., Yu, J., Kurihara, T., Li, K., Niu, Z., & Zhan, S. (2021). Learning an optical filter for green pepper automatic picking in agriculture. *Computers and Electronics in Agriculture*, *191*, 106521. https://doi.org/10.1016/j.compag.2021.106521

Liu, Y., Huang, Y., & Li, R. (2017). Innovative hyperspectral imaging-based techniques for quality evaluation of fruits and vegetables. *Applied Sciences*, *7*(2), 189. https://doi.org/10.3390/app7020189

Lu, N., Han, P., & Wang, J. H. (2017). Application of hyperspectral imaging in non-destructive testing of fruits and vegetables. *Journal of Food Safety and Quality*, *8*, 4594–4601.

Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. *Neurocomputing*, *267*, 378–384. https://doi.org/10.1016/j.neucom.2017.06.023

Lube, V., Noyan, M. A., Przybysz, A., Salama, K., & Blilou, I. (2022). MultipleXLab: A high-throughput portable live-imaging root phenotyping platform using deep learning and computer vision. *Plant Methods*, *18*, 38. https://doi.org/10.1186/s13007-022-00864-4

Mohd Ali, M., Hashim, N., Bejo, S. K., & Shamsudin, R. (2020). Comparison of laser backscattering imaging and computer vision system for grading of seedless watermelons. *Journal of Food Measurement and Characterization*, *14*, 69–77. https://doi.org/10.1007/s11694-019-00268-4

Momin, A., Kondo, N., Al Riza, D. F., Ogawa, Y., & Obenland, D. (2023). A methodological review of fluorescence imaging for quality assessment of agricultural products. *Agriculture (Montreal)*, *13*(7), 1433. https://doi.org/10.3390/agriculture13071433

Ndubisi, A. A., Liberty, J. T., Olatunbosun, O. S., Shoyombo, H. A., & Oyeniyi, S. K. (2022). Potential application of hyperspectral imaging in food grain quality inspection, evaluation, and control during bulk storage. *Journal of Agriculture and Food Research*, *8*, 100288. https://doi.org/10.1016/j.jafr.2022.100288

Neerja, X., & Renu, K. (2019). A review on rice grain quality evaluation: Current status and future prospects. *Food and Bioprocess Technology*, *13*(3), 567–586. https://doi.org/10.5772/intechopen.89367

Odek, Z.R., Siebenmorgen , T.J., & Saxena,, A. (2020). Fissuring kinetics of rough rice during the drying process. *Applied Engineering in Agriculture*, 36(5), 639–645.

Olakanmi, S., Karunakaran, C., & Jayas, D. (2023). Applications of X-ray micro-computed tomography and small-angle X-ray scattering techniques in food systems: A concise review. *Journal of Food Engineering*, *342*, 111355. https://doi.org/10.1016/j.jfoodeng.2022.111355

Olivares Díaz, E., Kawamura, S., Kato, M., Nagata, T., & Koseki, S. (2019). Combined use of a near-infrared spectrometer and a visible light grain segregator for accurate non-destructive determination of amylose content in rice. *Journal of Cereal Science*, *90*, 102848. https://doi.org/10.1016/j.jcs.2019.102848

Osornio-Rios, R. A., Antonino-Daviu, J. A., Romero-Troncoso, R., & de, J. (2019). Recent industrial applications of infrared thermography: A review. *IEEE Transactions on Industrial Informatics*, *15*(2), 615–625. https://doi.org/10.1109/TII.2018.2884738

Ponnusamy, V., Anand, P., & Bhatt, V. (2023). Classification of adulterated food grain thermal images using convolutional neural networks. In R. N. Shaw, M. Paprzycki & A. Ghosh (Eds.), *Advanced communication and intelligent systems. ICACIS 2022. Communications in computer and information science* (Vol. *1749*, pp. 475–480). Springer Cham. https://doi.org/10.1007/978-3-031-25088-0_42

Poornima, S. N., & Shantha, V. (2023). Automated testing for quality inspection of food grains. In G. Manik, S. Kalia, O. P. Verma, & T. K. Sharma (Eds.), *Lecture notes in mechanical engineering* (pp. 983–989). Springer. https://doi.org/10.1007/978-981-19-2188-9_89

Praprotnik, E., Vončina, A., Žigon, P., Knapič, M., Susič, N., Širca, S., Vodnik, D., Lenarčič, D., Lapajne, J., Žibrat, U., & Razinger, J. (2023). Early detection of wireworm (Coleoptera: Elateridae) infestation and drought stress in maize using hyperspectral imaging. *Agronomy*, *13*(1), 178. https://doi.org/10.3390/agronomy13010178

Qandil, H., Wang, S., & Zhao, W. (2019). Application-based design of the Fresnel lens solar concentrator. *Renewables: Wind, Water, and Solar*, *6*(1), 1–13.

Rabanera, J. D., Guzman, J. D., & Yaptenco, K. F. (2021). Rapid and non-destructive measurement of moisture content of peanut (Arachis hypogaea L.) kernels using a near-infrared hyperspectral imaging technique. *Journal of Food Measurement and Characterization*, *15*(4), 3069–3078. https://doi.org/10.1007/s11694-021-00894-x

Ramirez, M., Singh, B., & Singh, V. (2019). Visible/near-infrared spectroscopy for grain quality evaluation: A review. *Trends in Food Science Technology*, *72*, 19–30.

Rathnayake, H. A., Navaratne, S. B., & Navaratne, C. M. (2018). Porous Crumb Structure of Leavened Baked Products. *International Journal of Food Science*, *2018*, 8187318. https://doi.org/10.1155/2018/8187318

Ravikant, L., Jayas, S. D., Noel, D. G. W., Paul, G. F., & Da-Wen, S. (2017). Extraction of spectral information from hyperspectral data and application of hyperspectral imaging for food and agricultural products. *Food Bioprocess Technology*, *10*(1), 1–33.

Scheffer, D. (2007). *Endoscopes use CMOS image sensors* Retrieved July 28, 2020, from https://www.vision-systems.com/home/article/16750278/endoscopes-use-cmos-image-sensors

Sendin, K., Manley, M., & Williams, P. J. (2018). Classification of white maize defects with multispectral imaging. *Food Chemistry*, *243*, 311–318. https://doi.org/10.1016/j.foodchem.2017.09.133

Senthilkumar, T., Jayas, D. S., White, N. D. G., Fields, P. G., & Gräfenhan, T. (2016). Detection of fungal infection and Ochratoxin A contamination in stored barley using near-infrared hyperspectral imaging. *Biosystems Engineering*, *147*, 162–173. https://doi.org/10.1016/j.biosystemseng.2016.03.010

Seo, Y., Umeda, S., & Yoshikawa, N. (2023). Environmental impact of agricultural sprayers used in Japanese rice farming. *International Journal of Agricultural Sustainability*, *21*(1, 2247803. https://doi.org/10.1080/14735903.2023.2247803

Shahin, M. A., Hatcher, D. W., & Symons, S. J. (2012). Development of multispectral imaging systems for quality evaluation of cereal grains and grain products. In D.-W. Sun (Ed.), *Computer vision technology in the food and beverage industries* (pp. 451–482). Woodhead Publishing. https://doi.org/10.1533/9780857095770.3.451

Sharma, A., Singh, T., & Garg, N. (2024). Nondestructive identification of wheat seed variety and geographical origin using near-infrared hyperspectral imagery and deep learning. *Journal of Chemometrics*, *38*, e3585. https://doi.org/10.1002/cem.3585

Shen, F., Zhao, T., Jiang, X., Liu, X., Fang, Y., Liu, Q., Hu, Q., & Liu, X. (2019). On-line detection of toxigenic fungal infection in wheat by visible/near infrared spectroscopy. *LWT*, *109*, 216–224. https://doi.org/10.1016/j.lwt.2019.04.019

Shetty, N., Olesen, M. H., Gislum, R., Deleuran, L. C., & Boelt, B. (2012). Use of partial least squares discriminant analysis on visible-near infrared multispectral image data to examine germination ability and germ length in spinach seeds. *Journal of Chemometrics*, *26*, 462–466. https://doi.org/10.1002/cem.1415

Steve, W. (2006). *Digital compositing for film and video*. Focal Press ISBN 0-240-80760-X.

Su, W. -H., Fennimore, S. A., & Slaughter, D. C. (2019). Fluorescence imaging for rapid monitoring of translocation behavior of systemic markers in snap beans for automated crop/weed discrimination. *Biosystems Engineering*, *186*, 156–167. https://doi.org/10.1016/j.biosystemseng.2019.07.009

Suman, T., & Dhruvakumar, T. (2015). Classification of paddy leaf diseases using shape and colour features. *International Journal of Electrical and Electronics Engineers*, *7*(1), 239–250.

Sun, G., Yang, K., Zhang, C., Wu, D., He, Y., & Feng, L. (2009). Identification of barley scab based on multi-spectral imaging technology. *Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering*, *25*(suppl. 2), 204–207. https://doi.org/10.3969/j.issn.1002-6819.2009.z2.039

Sun, H., Zhang, L., Li, H., Rao, Z., & Ji, H. (2021). Nondestructive identification of barley seeds varieties using hyperspectral data from two sides of barley seeds. *Journal of Food Process Engineering*, *44*(8), e13769. https://doi.org/10.1111/jfpe.13769

Sun, Y., Ye, Z., Zhong, M., Wei, K., Shen, F., Li, G., Yuan, J., & Xing, C. (2023). Rapid and nondestructive method for identification of molds growth time in wheat grains based on hyperspectral imaging technology and chemometrics. *Infrared Physics Technology*, *128*, 104532. https://doi.org/10.1016/j.infrared.2022.104532

Talaviya, T., Shah, D., Patel, N., Yagnik, H., & Shah, M. (2020). Implementation of artificial intelligence in agriculture for optimization of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, *4*, 58–73. https://doi.org/10.1016/j.aiia.2020.04.002

Teena, M., Manickavasagan, A., Al-Sadi, A., Al-Yahyai, R., Deadman, M., & Al-Ismaili, A. (2016). RGB color imaging to detect Aspergillus flavus infection in dates. *Emirates Journal of Food and Agriculture*, *28*(1), 683. https://doi.org/10.9755/ejfa.2016-01-070

Terensan, S., Salgadoe, A. S. A., Kottearachchi, N. S., & Weerasena, O. V. D. S. J. (2024). Proximally sensed RGB images and colour indices for distinguishing rice blast and brown spot diseases by k-means clustering: Towards a mobile application solution. *Smart Agricultural Technology*, *9*, 100532. https://doi.org/10.1016/j.atech.2024.100532

Umul, Y. Z. (2008). The relation between the boundary diffraction wave theory and physical optics. *Optics Communications*, *281*(19), 4844–4848. https://doi.org/10.1016/j.optcom.2008.06.072

Vadivambal, R., & Jayas, D. S. (2011). Applications of thermal imaging in agriculture and food industry—A review. *Food and Bioprocess Technology*, *4*, 186–199. https://doi.org/10.1007/s11947-010-0333-5

Vollmer, M. (2021). Infrared Thermal Imaging. In K. Ikeuchi (Ed.), *Computer vision* (pp. 666–670). Springer, Cham. https://doi.org/10.1007/978-3-030-63416-2_844

Wang, F., Gao, J., & Zha, Y. (2018). Hyperspectral sensing of heavy metals in soil and vegetation: Feasibility and challenges. *ISPRS Journal of Photogrammetry and Remote Sensing*, *136*, 73–84. https://doi.org/10.1016/j.isprsjprs.2017.12.003

Wang, J., Li, S., An, Z., Jiang, X., Qian, W., & Ji, S. (2019). Batch-normalized deep neural networks for achieving fast intelligent fault diagnosis of machines. *Neurocomputing*, *329*, 53–65. https://doi.org/10.1016/j.neucom.2018.10.049

Wang, Y., & Song, S. (2023). Variety identification of sweet maize seeds based on hyperspectral imaging combined with deep learning. *Infrared Physics and Technology*, *130*, 104611. https://doi.org/10.1016/j.infrared.2023.104611

Wang, M., Xu, Y., Yang, Y., Mu, B., Nikitina, M. A., & Xiao, X. (2022). Vis/NIR optical biosensors applications for fruit monitoring. *Biosensors and Bioelectronics: X*, *11*, 100197. https://doi.org/10.1016/j.biosx.2022.100197

Weng, S., Tang, P., Yuan, H., Guo, B., Yu, S., Huang, L., & Xu, C. (2020). Hyperspectral imaging for accurate determination of rice variety using a deep learning network with multi-feature fusion. *Spectrochemical Act Part A: Molecular and Biomolecular Spectroscopy*, *234*, 118237. https://doi.org/10.1016/j.saa.2020.118237

Xu, Q. F., Wang, W. W., Liu, B. Q., Yang, D., He, Y. M., Sui, X. Y., Sun, T. K., Wu, J. P., & Zhou, G. D. (2017). Effects of pest control on rice productivity in different climatic regions of China. *PLoS One*, *12*, e0188753. https://doi.org/10.1371/journal.pone.0188753

Yipeng, L., Wenbing, L., Kaixuan, H., Wentao, T., Ling, Z., Shizhuang, W., & Linsheng, H. (2022). Determination of wheat kernels damaged by Fusarium head blight using monochromatic images of effective wavelengths from hyperspectral imaging coupled with an architecture self-search deep network. *Food Control*, *135*, 108819. https://doi.org/10.1016/j.foodcont.2022.108819

Yoon, S., Kim, M., Jang, M., Choi, Y., & Kang, S. (2020). Deep optical imaging within complex scattering media. *Nature Reviews Physics*, *2*, 141–158. https://doi.org/10.1038/s42254-019-0143-2

Yoshioka, O., Nakayama, M., Noguchi, Y., & Horie, H. (2013). Use of image analysis to estimate anthocyanin and UV-excited fluorescent phenolic compound levels in strawberry fruit. *Breeding Science*, *63*(2), 211–217. https://doi.org/10.1270/jsbbs.63.211

Zahra, N., Hafeez, M. B., Nawaz, A., & Farooq, M. (2022). Rice production systems and grain quality. *Journal of Cereal Science*, *105*, 103463. https://doi.org/10.1016/j.jcs.2022.103463

Zareef, M., Arslan, M., Hassan, M., Ahmad, W., Ali, S., Li, H., Ouyang, Q., Wu, X., Muhammad, M, & Chen, Q. (2021). Recent advances in assessing qualitative and quantitative aspects of cereals using nondestructive techniques: A review. *Trends in Food Science Technology*, 116, 815–828. https://doi.org/10.1016/j.tifs.2021.08.012

Zhang, G. X. (2021). Machine learning in X-ray imaging and microscopy applications. *Advanced X-Ray Imaging of Electrochemical Energy Materials and Devices*, *205*, 221. https://doi.org/10.1007/978-981-16-5328-5_9

Zhang, J., Li, M., Sun, Z., Liu, H., Sun, H., & Yang, W. (2018). Chlorophyll Content Detection of Field Maize Using RGB-NIR Camera. *IFAC-PapersOnLine*, *51*(17), 700–705. https://doi.org/10.1016/j.ifacol.2018.08.114

Zhang, H., Liu, Z. G., Yin, Y. X., Liu, Y. Q., Fei, O. U. J. A., & Technology, T., et al. (2019). Determination of cadmium in Chinese herbal medicine by energy dispersive X-ray fluorescence spectrometry. *Analytical Testing Technology and Instruments*, *25*, 191–195. https://doi.org/10.16495/j.1006-3757.2019.03.009

Zhang, S., Liu, S., Shen, L., Chen, S., He, L., & Liu, A. (2022). Application of near-infrared spectroscopy for the nondestructive analysis of wheat flour: A review. *Current Research in Food Science*, *5*, 1305–1312. https://doi.org/10.1016/j.crfs.2022.08.006

Zhao, L. -J., Xie, J. -F., Zhang, H., Wang, Z. -T., Jiang, H. -J., & Gao, S. -L. (2018). Enzymatic activity and chlorophyll fluorescence imaging of maize seedlings (Zea mays L.) after exposure to low doses of chlorsulfuron and cadmium. *Journal of Integrative Agriculture*, *17*(4), 826–836. https://doi.org/10.1016/S2095-3119(17)61717-9

Zhongzhi, H. (2019). *Computer vision-based agriculture engineering* (1st ed.). CRC Press. https://doi.org/10.1201/9780429289460

Zhou, W., Zhang, J., Zou, M., Liu, X., Du, X., Wang, Q., & Li, J. (2019). Feasibility of using rice leaves hyperspectral data to estimate CaCl2-extractable concentrations of heavy metals in agricultural soil. *Scientific Reports*, *9*(1), 16084. https://doi.org/10.1038/41598-019-52503

Zhu, D., Han, J., Liu, C., Zhang, J., & Qi, Y. (2025). Vis-NIR and NIR hyperspectral imaging combined with convolutional neural network with attention module for flaxseed varieties identification. *Journal of Food Composition and Analysis*, *137*(A), 106880. https://doi.org/10.1016/j.jfca.2024.106880