

MINI REVIEW

Importance of Hyperspectral Imaging for Hidden Pest Infestation Detection in Fruits, Vegetables and Grains

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Abstract

Hidden insect infestations in fruits, vegetables, and grains are a major cause of postharvest losses and pose significant challenges to food quality, quarantine inspection, and international trade. Since internal-feeding pests develop within host tissues without producing visible external symptoms, conventional inspection methods are often inadequate for their early detection. Hyperspectral imaging (HSI) has emerged as a powerful non-destructive technology that integrates imaging and spectroscopy to detect subtle biochemical, physiological, and structural changes associated with concealed insect infestation. By acquiring spectral information across the visible, near-infrared, and short-wave infrared regions, HSI enables rapid and accurate identification of infested commodities before visible damage occurs. The integration of machine learning and deep learning algorithms has further enhanced the sensitivity and automation of HSI-based detection systems. This review highlights the principles of hyperspectral imaging, its applications in detecting hidden pest infestations in major fruits, vegetables, and stored grains, recent advances in artificial intelligence-assisted analysis, and future prospects for precision agriculture and postharvest quality management. The technology offers considerable potential to improve pest surveillance, reduce postharvest losses, strengthen quarantine measures, and promote sustainable crop protection through rapid, non-invasive, and high-throughput detection systems.

Keywords: Hyperspectral imaging; hidden pest detection; concealed infestation; fruits; vegetables; grains; non-destructive sensing; precision agriculture; artificial intelligence.

Introduction

Global agricultural production is continually threatened by insect pests that cause significant losses both in the field and during postharvest storage (Shahbazi et al., 2025). Among these, hidden or concealed insect infestations represent one of the greatest challenges because they develop internally within fruits, vegetables, seeds, and grains without producing obvious external symptoms during the

early stages of infestation (Souza et al., 2025). Internal feeders such as fruit borers, fruit flies, seed borers, grain weevils, and beetle larvae consume host tissues while remaining protected inside the commodity, making visual inspection ineffective. Consequently, infested produce often enters storage facilities and marketing channels unnoticed, leading to deterioration in quality, reduced shelf life, economic losses, and restrictions in international

trade due to quarantine concerns (Arya et al., 2026). Conventional methods used for detecting concealed infestations include manual inspection, destructive sampling, X-ray radiography, magnetic resonance imaging (MRI), computed tomography (CT), and acoustic sensing (Keerthana, et al., 2025; Patel et al., 2026). Although these techniques have contributed significantly to pest detection, each possesses inherent limitations (Table 1). Visual inspection is subjective and incapable of detecting internal infestations (Khan et al., 2025). Destructive sampling is labour-intensive and unsuitable for large-scale commercial screening. Similarly, CT and MRI provide excellent internal visualization but require expensive instrumentation, specialized facilities, and prolonged scanning times that limit their practical application in routine agricultural inspection. Hyperspectral imaging (HSI) has emerged over the past two decades as one of the most promising non-invasive technologies for early detection of hidden insect infestations (Cheng et al., 2025). Unlike conventional imaging systems that capture only three colour bands (red, green, and blue), hyperspectral imaging simultaneously acquires hundreds of contiguous narrow spectral bands across the visible (VIS), near-infrared (NIR), and short-wave infrared (SWIR) regions (Hong et al., 2026). Each pixel within the image contains a complete reflectance spectrum that represents the biochemical and structural characteristics of the sampled tissue. Since insect feeding induces subtle physiological, biochemical, and structural changes long before visible symptoms appear, hyperspectral imaging can detect these alterations with remarkable sensitivity. Consequently, HSI has become an indispensable tool in precision agriculture, smart postharvest management, food safety, and quarantine inspection (Doruchowski et al., 2025).

Principle of Hyperspectral Imaging

Hyperspectral imaging combines the principles of digital imaging and spectroscopy into a single analytical platform capable of collecting both spatial and spectral information simultaneously. Traditional imaging records only spatial information, whereas spectroscopy measures only the spectral characteristics of a sample without preserving its spatial distribution. Hyperspectral imaging integrates both approaches by generating a three-dimensional dataset known as a hyperspectral cube or hypercube, consisting of two spatial dimensions (x and y) and one spectral dimension (λ) (Li et al., 2025; Silva et al., 2025). Each material interacts with electromagnetic radiation in a unique manner depending on its chemical composition, moisture content, cellular architecture, and surface characteristics. When incident light strikes a biological sample, part of the radiation is absorbed while the remainder is reflected, transmitted, or scattered. These interactions generate characteristic spectral fingerprints that can be measured across hundreds of wavelengths (Luo et al., 2025). Healthy plant tissues exhibit spectral signatures determined by pigments such as chlorophyll, carotenoids, anthocyanins, water molecules, carbohydrates, proteins, cellulose, lignin, and waxes. When insects infest plant tissues, their feeding activity disrupts cellular organization, alters moisture distribution, stimulates defensive metabolism, and accelerates tissue degradation (Raghav et al., 2026). These biochemical changes modify the reflectance spectrum of the tissue. Because hyperspectral imaging measures reflectance continuously across hundreds of wavelengths, even minute physiological alterations associated with early insect infestation become detectable before any visual symptoms are evident.

Table 1. Comparison of Hyperspectral Imaging with Traditional Detection Methods for Hidden Pest Detection

Parameter	Visual Inspection	Destructive Sampling	X-ray Radiography	CT/MRI Imaging	Acoustic Sensing	Hyperspectral Imaging (HSI)
Detection principle	External visual symptoms	Cutting/opening commodity	X-ray penetration to visualize internal structures	Cross-sectional internal imaging	Detection of insect feeding or movement sounds	Detection of biochemical and structural changes through spectral signatures
Nature of method	Non-destructive	Destructive	Non-destructive	Non-destructive	Non-destructive	Non-destructive
Detection of hidden infestation	Very poor	Excellent	Good	Excellent	Moderate	Excellent
Early detection before visible symptoms	No	Limited	Moderate	Moderate	Limited	Excellent
Detection basis	Visible damage	Direct observation of insects	Density differences	Internal anatomical structures	Acoustic emissions	Physiological, biochemical, moisture, and structural alterations
Spatial information	Yes	Yes	Yes	Yes (3D)	No	Yes
Spectral/Chemical information	No	Limited	No	Limited	No	Yes (hundreds of spectral bands)
Automation potential	Low	Low	Moderate	Moderate	Moderate	Very high using AI and deep learning
Screening speed	High	Low	Moderate	Low	Moderate	High
Suitability for large-scale commercial inspection	Moderate	Poor	Moderate	Poor	Moderate	Excellent
Need for sample destruction	No	Yes	No	No	No	No
Equipment cost	Very low	Low	High	Very high	Moderate	High (decreasing with technological advances)
Operational complexity	Low	Low	Moderate	High	Moderate	Moderate to High
Labour requirement	High	High	Moderate	High	Moderate	Low after automation

Compatibility with AI/ML	Minimal	Minimal	Moderate	Moderate	Moderate	Excellent (SVM, CNN, ResNet, Vision Transformers, etc.)
Major limitations	Cannot detect internal infestation; subjective	Time-consuming; unsuitable for commercial screening	Limited biochemical information	Expensive equipment, specialized facilities, slow scanning	Influenced by insect activity & environmental noise	Large datasets require advanced computation and specialized sensors

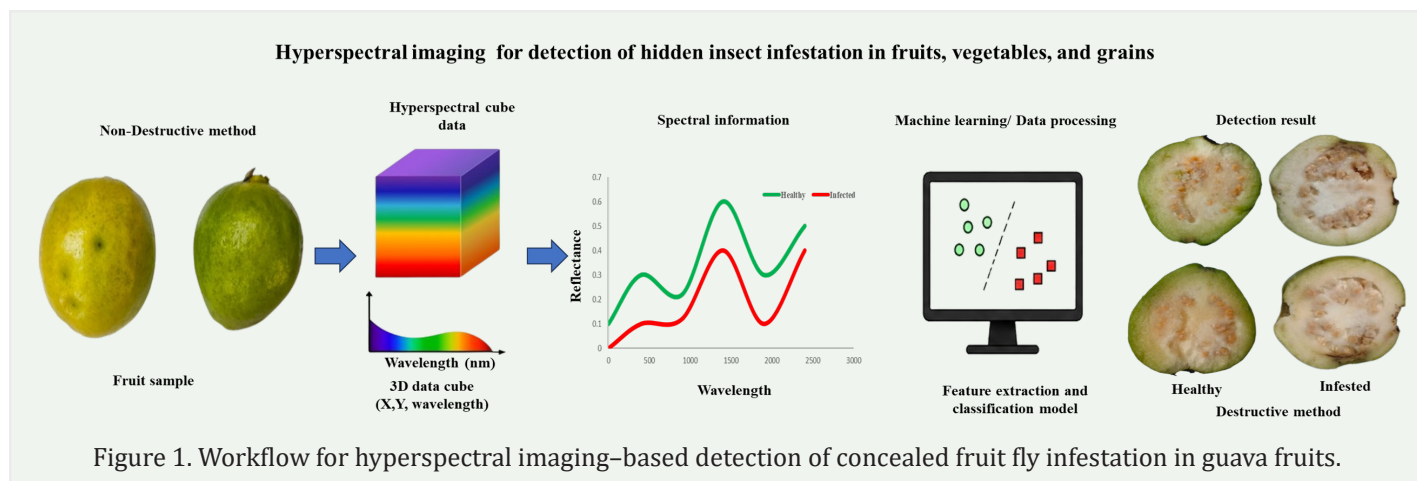
Physiological Basis of Hidden Pest Detection

Hidden insect infestation triggers a cascade of physiological and biochemical responses within host tissues. Feeding larvae consume internal cells, resulting in destruction of vascular tissues, degradation of starch reserves, breakdown of cell walls, reduction in chlorophyll concentration, moisture loss, oxidation of phenolic compounds, and accumulation of stress-related metabolites (Sonowal et al., 2026). Simultaneously, insect respiration and metabolic waste products alter the internal gaseous environment of the host tissue. These processes produce measurable changes in optical properties. Cell collapse increases light scattering, while moisture depletion alters absorption characteristics within the near-infrared region. Changes in carbohydrate metabolism influence reflectance in wavelengths associated with C-H, O-H, and N-H molecular bonds. Furthermore, oxidative stress induced by insect feeding stimulates synthesis of phenolics, flavonoids, terpenoids, and volatile organic compounds (VOCs), all of which contribute to distinctive spectral signatures (Pfordt and Paulus, 2025). Consequently, hyperspectral imaging serves as an indirect indicator of insect activity by detecting these physiological alterations rather than imaging the insects themselves. This capability explains why HSI can identify concealed infestations several days before visible damage or

emergence holes become apparent.

Spectral Regions Used in Hidden Pest Detection

The effectiveness of hyperspectral imaging largely depends on the spectral region employed for data acquisition. Different wavelength ranges provide complementary information regarding the biochemical composition and structural characteristics of agricultural commodities (Yan et al., 2026) (Table 1). The visible region (400–700 nm) primarily reflects pigment composition, including chlorophylls, carotenoids, and anthocyanins. Early insect feeding often causes pigment degradation, making this region valuable for detecting physiological stress (Elmaidomy et al., 2026). The near-infrared region (700–1000 nm) provides information related to cellular architecture, internal tissue structure, and scattering properties. Since concealed insect feeding disrupts cellular organization, this spectral range is particularly useful for identifying internal damage (Huang et al., 2025). The short-wave infrared region (1000–2500 nm) is sensitive to molecular vibrations associated with water, carbohydrates, proteins, lipids, cellulose, and lignin (Raghav et al., 2026). Hidden insect infestation modifies these biochemical constituents through tissue degradation, making SWIR wavelengths highly informative for detecting internal infestations. Modern hyperspectral systems often combine VIS-NIR and SWIR imaging



to maximize detection accuracy across diverse commodities (Faqeerzada et al., 2025).

Applications in Fruit Crops

Fruit crops represent one of the most important applications of hyperspectral imaging because many economically important pests develop entirely within fruits. Fruit fly larvae, fruit borers, seed borers, and internal-feeding moth larvae remain concealed until late developmental stages, making quarantine inspection particularly challenging (Table 1). In apples, hyperspectral imaging has successfully detected codling moth infestations by identifying localized changes in moisture distribution, tissue density, and biochemical composition (Shao et al., 2026). Similar success has been achieved for citrus fruits infested by fruit flies, where larval feeding alters internal pulp structure without producing immediate external symptoms (Xie et al., 2026). In mango, HSI has demonstrated remarkable sensitivity for identifying infestation by Oriental fruit fly (*Bactrocera dorsalis*). Larval feeding causes degradation of pulp tissues, reduction in moisture content, and increased enzymatic activity, all of which generate characteristic spectral changes detectable during early infestation (Chaudhary et al., 2025). Litchi presents a particularly challenging case because larvae of the litchi fruit borer

(*Conopomorpha sinensis*) develop inside developing fruits, causing substantial economic losses while remaining externally invisible. Conventional grading frequently fails to distinguish healthy fruits from infested ones. Hyperspectral imaging offers significant potential for early detection of concealed larval infestation by monitoring spectral changes associated with tissue degradation, moisture redistribution, and metabolic alterations. Such technology could substantially improve export quality inspection and reduce postharvest losses in litchi-producing regions (Zhao et al., 2026).

Applications in Vegetables

Hidden infestations are equally important in vegetables (Table 1), particularly in crops such as tomato, brinjal, potato, onion, pepper, and cucurbits. Internal feeders consume fruit tissues, reduce market quality, and accelerate microbial infections (Xie et al., 2026). Hyperspectral imaging enables early recognition of these infestations through detection of localized physiological stress. In tomatoes, larval feeding by fruit borers alters chlorophyll degradation patterns and water distribution, producing distinct spectral responses. Similarly, wireworm infestation in potato tubers induces starch degradation and tissue necrosis that become detectable through near-infrared imaging long before external lesions develop (Yang et al.,

Table 2. Applications of Hyperspectral Imaging for Detection of Hidden Pest Infestations in Fruits, Vegetables, and Grains

Sl no	Commodity	Hidden pest	Nature of infestation	Spectral range (nm)	Hyperspectral imaging approach	Data analysis / AI model	Major findings
1	Apple	Codling moth (<i>Cydia pomonella</i>)	Larvae tunnel inside fruit pulp and seed cavity	400–900	Diffuse reflectance HSI	LDA, Decision Tree, KNN, PLS-DA, ANN	Successfully discriminated healthy and infested fruits; classification accuracy >85% depending on model. (University of Kentucky)
2	Mango	Oriental fruit fly (<i>Bactrocera dorsalis</i>)	Internal larval feeding within pulp	400–1000	Reflectance and absorbance HSI	Discriminant Analysis (DA)	Early detection before visible symptoms with accuracies approaching 99%. (PMC)
3	Orange	Internal fruit fly infestation	Internal pulp degradation	400–1000	Reflectance HSI	PCA, Binary Regression	100% discrimination between healthy and infested samples under experimental conditions. (PMC)
4	Grapefruit	Citrus leafminer (<i>Phyllocnistis citrella</i>)	Internal leaf mining	450–930		Spectral Information Divergence (SID)	Detection accuracy of approximately 95%. (PMC)
5	Jujube	<i>Carposina niponensis</i>	Internal fruit infestation	900–1700		Binary Regression	Healthy and infested fruits classified with >93% accuracy. (PMC)
6	Tomato	Tomato fruit borer (<i>Helicoverpa armigera</i>)	Internal fruit feeding	VIS–NIR		SVM, CNN	Detects biochemical changes associated with larval feeding before external symptoms become obvious. (PubMed)
7	Potato	Wireworms	Internal tunnelling in tubers	VIS–NIR/SWIR		PLS-DA, Random Forest	Sensitive to internal tissue degradation and moisture redistribution. (PubMed)
8	Brinjal	Shoot and fruit borer (<i>Leucinodes orbonalis</i>)	Internal fruit damage	VIS–NIR		CNN	Potential for identifying concealed larval infestation through tissue spectral changes. (PubMed)
9	Litchi	Fruit borer (<i>Conopomorpha sinensis</i>)	Internal seed and pulp feeding	VIS–NIR/SWIR		Deep learning (potential)	High potential for quarantine inspection by detecting internal tissue degradation and moisture changes before visible damage; commercial application remains an active research opportunity. (PMC)

10	Wheat	Rice weevil (<i>Sitophilus oryzae</i>)	Larvae develop completely inside kernels	VIS–NIR	Kernel-level HSI	Spectral pre-processing + feature selection + machine learning	Enables nondestructive identification of hidden infestations at different developmental stages. (PMC)
11	Wheat	Lesser grain borer (<i>Rhyzopertha dominica</i>)	Internal kernel feeding	NIR HSI	Reflectance HSI	ANN, SVM	Detects concealed infestation through changes in kernel spectra. (PubMed)
12	Maize	Maize weevil (<i>Sitophilus zeamais</i>)	Internal grain infestation			Backpropagation Neural Network	Accurate discrimination of infested kernels using selected wavelengths. (PMC)
13	Rice	Rice weevil (<i>Sitophilus oryzae</i>)	Internal grain feeding	VIS–NIR		Deep learning, SVM	Early detection before adult emergence, reducing storage losses. (PubMed)
14	Pulses	Pulse beetles (<i>Callosobruchus spp.</i>)	Larval feeding inside seeds	VIS–NIR		PLS-DA, Random Forest	Potential for rapid seed screening and quality grading. (PMC)

2025). Because vegetable quality depends heavily on internal texture and freshness, HSI provides valuable information not only for pest detection but also for simultaneous quality assessment during postharvest grading.

Applications in Stored Grains

Stored grain ecosystems present ideal conditions for concealed insect infestations because many beetles complete their larval development entirely within individual kernels (Table 1). Species such as the rice weevil (*Sitophilus oryzae*), maize weevil (*Sitophilus zeamais*), granary weevil (*Sitophilus granarius*), lesser grain borer (*Rhyzopertha dominica*), and pulse beetles (*Callosobruchus spp.*) cause severe postharvest losses worldwide (Kaliramesh et al., 2013; Chelladurai et al., 2014). Hyperspectral imaging detects internal grain infestation by measuring changes in moisture content, kernel density, starch composition, and protein degradation resulting from larval feeding. Studies have consistently reported classification accuracies exceeding 90–95% when hyperspectral imaging is integrated with

machine learning algorithms. Such systems enable rapid, non-destructive screening of thousands of kernels, making them highly suitable for grain storage facilities, seed certification laboratories, and quarantine inspection services.

Integration with Artificial Intelligence

One of the major strengths of hyperspectral imaging lies in its compatibility with artificial intelligence and machine learning (Table 2). Each hyperspectral image contains enormous amounts of spectral information, often comprising hundreds of wavelengths for every pixel. Manual interpretation of such datasets is impractical (Hong et al., 2026). Machine learning algorithms including Support Vector Machines (SVM), Random Forests, Partial Least Squares Discriminant Analysis (PLS-DA), Artificial Neural Networks (ANN), and K-Nearest Neighbours (KNN) efficiently classify healthy and infested samples based on spectral signatures. More recently, deep learning architectures such as Convolutional Neural Networks (CNNs), 3D-CNNs, ResNet, EfficientNet, and Vision Transformers have further improved classification accuracy

by automatically learning complex spatial-spectral relationships without extensive feature engineering. The combination of hyperspectral imaging and deep learning has enabled automated detection systems capable of real-time operation on industrial sorting lines, significantly advancing precision agriculture and intelligent food processing.

Future Perspectives

Future developments in hyperspectral imaging are expected to transform agricultural pest management. Advances in sensor miniaturization are leading to portable hyperspectral cameras suitable for handheld field diagnostics. Drone-mounted hyperspectral sensors are enabling rapid orchard-scale surveillance, while robotic harvesting systems equipped with hyperspectral cameras can simultaneously assess fruit maturity, quality, and pest infestation. Emerging technologies such as explainable artificial intelligence, cloud computing, Internet of Things (IoT), and digital twins will further enhance decision-making by integrating hyperspectral data with environmental, meteorological, and crop management information. Multisensor platforms combining hyperspectral imaging with thermal imaging, Raman spectroscopy, fluorescence imaging, and X-ray imaging are expected to provide even greater diagnostic accuracy for complex pest detection scenarios. As computational efficiency improves and instrument costs decline, hyperspectral imaging is likely to become a routine component of smart agriculture, precision horticulture, postharvest quality control, and biosecurity surveillance.

Conclusion

Hyperspectral imaging has revolutionized the detection of hidden insect infestations by providing a rapid, accurate, and non-destructive

means of assessing the internal health of agricultural commodities. Its ability to detect subtle biochemical and structural changes induced by concealed insect feeding offers significant advantages over conventional inspection methods, enabling intervention before visible damage becomes apparent. The integration of hyperspectral imaging with machine learning and artificial intelligence has further enhanced its potential for automated, real-time pest detection across fruits, vegetables, and stored grains. With continued advances in sensor technology, computational methods, and portable imaging systems, hyperspectral imaging is poised to become a cornerstone of next-generation precision agriculture, supporting sustainable pest management, minimizing postharvest losses, strengthening quarantine systems, and improving global food security.

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