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Review

Ensuring food security: Strategies for insect pest detection in storage - A review

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Abstract

The infestation of stored food grains by insect pests poses an important threat to global food security and economic stability. The loss of stored food grains may be due to insect pest infestation, microbial spoilage, or inadequate storage conditions. Among these losses, insect pest infestations cause major losses in stored food commodities. Therefore, early detection of storage pests is highly important to farmers and warehouse managers/owners. Conventional detection methods such as visual/manual inspection, grain probes and insect traps, pheromones, visual lures, and berlese funnel methods are time-consuming and destructive methods. As conventional detection requires repeated sampling and monitoring, the insect pests can be detected only after the adult emergence. At present, non-destructive methods, *viz.,* improved and advanced techniques such as hidden infestation detectors, NIR, X-ray imaging, uric acid analysis, microwave resonators, conductive roller mills, ELISA, acoustic detection, environmental sensing, electronic-nose methods, thermal imaging, solid-phase microextraction (SPME), and machine vision are explored for their potential in enhancing the efficiency and scalability of detection systems. The advantages and limitations of each method are critically assessed, considering factors such as accuracy, cost-effectiveness, and applicability in storage environments. The present review explores various improved and advanced detection techniques employed in the monitoring of insect pests in stored food commodities.

Introduction

Agriculture is the key component of livelihoods, and directly affects 19% of the world's population. Observations and projections indicate that by 2050, the world's population will reach approximately nine billion (Parfitt *et al*., 2010; Duro *et al.,* 2020). Food loss refers to a decrease in the quantity or quality of food intended for human consumption, occurring at various stages in the supply chain. This loss can result from factors such as spoilage, damage, contamination, or inefficiencies in handling, transportation, and storage, leading to a reduction in the amount of food available for consumption. Food loss contributes to resource waste and economic losses, and poses challenges in addressing global food security and sustainability (Spang *et al*., 2019; Keerthana *et al*., 2025). The majority of the anticipated rise in population growth is expected to occur in developing nations, many of which are already experiencing starvation and malnutrition. The escalating factors of climate change and urbanisation further exacerbate concerns about the rising demand for food. Over the past few decades, many countries have prioritised enhancing agricultural production, changing land use patterns, and implementing population control measures to address the growing food demand (Kumar and Kalita, 2017). Owing to these fluctuations in the population, there is a strong need to increase the food production rate by 60 - 70% to fulfil the growing demands of the world's growing population. The production of crops in agriculture is hampered by various abiotic and biotic factors. Biotic factors include insects, weeds,

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pathogens, and other nematodes. They cause approximately 20 - 40% crop loss. It is estimated that only 18 - 20% of the crops produced worldwide are destroyed by insects, which leads to quantitative and qualitative food loss (FAO, 2019). Approximately, 33% of the globally produced food, equivalent to approximately 1.3 billion tons and valued at approximately US $1 trillion, is lost each year during postharvest operations.

Addressing postharvest losses (PHL) is essential for improving food security, reducing waste, and enhancing the efficiency of the food supply chain (Bendinelli *et al*., 2020). The PHL remains a critical concern, as in field and storage godowns. Globally, it is quite common for plants to experience PHL of grains ranging from 10 - 15% (Hassan *et al*., 2023). In India, the storage loss of cereals is estimated to be approximately 0.75 to 1.21%, and for pulses and oilseeds, it varies from 1.18 to 1.67% and 0.22 to 1.61%, respectively (Ahmad *et al*., 2021). Stored grain insect pests pose a major threat to food security and economic stability. In food grain storage, insect infestations result in quantitative and qualitative losses, diminishing the overall value of the food grain. Storage grain pests not only feed on stored food grains, but also introduce contaminants in the form of their metabolic wastes and their body parts. The metabolic activities of insects generate heat and moisture, accelerating the growth of microorganisms, and creating hotspot areas within stored grains. Grains heavily affected by insect infestations become unsuitable for seeding purposes, and their derived metabolites make food grains unfit for human consumption (Srivastava and Mishra, 2021).

Various techniques have been employed for identifying insects in grains, including conventional approaches such as visual examination, grain probes and insect traps (Mohan and Fields, 2002; Mohan and Rajesh, 2016), visual lures, pheromones, pitfall traps, and the berlese funnel method. However, many of these detection techniques exhibit limitations, including destructiveness, inaccuracy, time-intensive processes, and an inability to discern internal insect infestations. Internal insect infestations can also be detected by improved and advanced technologies, *viz*. hidden infestation detectors, X-ray analysis (Karunakaran *et al*., 2004b), near-infrared reflectance (NIR) analysis (Crépon *et al*., 2023), uric acid analysis (Liu *et al.*, 2022), immunoassay biochemical tests, microwave resonators, conductive roller mills (Brabec *et al*., 2023), and in recent years, sensor-based detection systems (Eliopoulos *et al*., 2015; Njoroge *et al*., 2019; Mankin *et al*., 2021), E-noses (Zhou *et al*., 2021), solid-phase microextraction methods, machine vision (Liu and Chahl, 2018), and environmental sensing have emerged as promising tools to increase the precision, efficiency, and timeliness of identifying stored-grain insect pests.

Monitoring stored food grains helps to track insect population trends, developmental stages, and infestation levels over time. The present review provides insights into insect activity in relation to environmental conditions, and can be used to evaluate the effectiveness of pest management strategies. These efforts underscore the importance of improved and advanced detection technologies by linking to and monitoring broader food security goals. To minimise losses and ensure safe storage for sustainable agricultural production, it is essential to develop improved and advanced methods for detecting insect infestations with increased sensitivity. Therefore, the present review aims to provide a thorough summary of improved and advanced techniques for detecting insects in stored food grains, emphasising their potential to enhance food security and sustainability.

Methods of detecting stored-grain pest infestations

Stored insect pests pose a significant threat to agricultural produce, stored food grains, and processed foods, causing substantial economic losses and health risks (Hamel *et al*., 2020). Timely and accurate detection of infestations is crucial for implementing effective pest management strategies. Various methods are employed to monitor stored insect pests and mitigate their impact on stored food grains.

Improved methods for detection of stored-grain pests

Detection of insects on basis of density

Hidden infestation detector

Hidden infestation detectors are innovative tools designed to identify and monitor pest activity within stored grain without extensive visual/manual inspection. It comprises of three stacked circular plates, with the upper and middle plates being determined to facilitate easy operation when lifted. The base plate was equipped with filter paper treated with ninhydrin. Samples of grains with a moisture level of approximately 20% were placed into the holes in the middle plate. These grains were crushed by pressing on the top plate, and colour changes in the infested grains were observed (Banga *et al*., 2018). A detector was used to test sorghum affected by *Sitophilus oryzae*, wheat infested with the Angoumois grain moth *Sitotroga cerealella*, and green gram harbouring the pulse beetle, *Callosobruchus maculatus* (Jamshidi *et al*., 2019).

Uric acid analysis

Insects that thrive in environments with limited moisture, such as stored product insects, eliminate uric acid as the final by-product of their nitrogen metabolism (Das *et al*., 2021). Uric acid, a key component found in the excrement of insects, has been suggested as a marker for identifying insect infestations in stored food grains. This approach indirectly identifies insect infestations throughout the storage period (Rajendran, 2005). Various techniques have been developed for assessing uric acid levels, including gas-liquid chromatography (GLC), paper chromatography, colorimetry, fluorometry, high-performance liquid chromatography (HPLC), thin-layer chromatography (TLC), and enzymatic methods (Banga *et al*., 2018). Using HPLC, uric acid estimation was performed in *Sitophilus granarius*, *Rhyzopertha dominica* (Zakladnoy *et al*., 2022), and *S. oryzae* (Zakladnoy and Yaitskikh, 2020), and uric acid analysis of *Triboliuum castaneum* was performed *via* the enzymatic UV method. Uric acid analysis was performed *via* high-performance liquid chromatography-diode array detection (HPLC-DAD) in cereals and pulses infested by stored-product insects (Das *et al*., 2021). According to the Bureau of Indian Standards (BIS, 1970), the colorimetric approach is suitable for measuring uric acid to ascertain the extent of infestation.

Detection of insects using non-imaging method

Near-infrared (NIR) reflectance spectroscopy

Near-infrared (NIR) spectroscopy has emerged as a quick, dependable, precise, and cost-effective method used for analysing the composition of grains (Losel *et al*., 2024), whereas classical NIR absorption spectroscopy enables the determination of concentrations of components such as water, carbohydrates, fats, and proteins (Shi *et al*., 2024). The principle involved in NIR spectroscopy is the interaction between NIR light and a sample. The NIR relies on the absorption of electromagnetic wavelengths ranging between 780 and 2,500 nm (Adedeji *et al*., 2020). This technique relies on the absorption, reflection, and transmission of NIR light by a sample, providing valuable information about the molecular structure and composition of the food grain sample. By examining the unique spectral patterns in the NIR region, NIR spectroscopy allows for the identification and quantification of various components within a sample, making it a versatile and widely utilised analytical tool in the field of agriculture (Johnson, 2020). An automated NIR spectroscopy system with wavelengths ranging from 400 to 1700 nm was used, and the larvae and pupae of rice weevil *S. oryzae* were observed with accuracy ranging between 92 and 93% (Maghirang *et al.*, 2003). The Indian meal moth, *Plodia interpunctella*, which infest stored rice commodities, was detected *via* NIR spectroscopy. SIMCA and PLS-DA have been used as classification methods to distinguish stored rice products from infested and uninfested *P. interpunctella*. The classification rate was 95.6% for uninfested samples, and 95% for infested samples when PLS-DA classifiers were used, whereas when SIMCA classification was used, it was 97% for infested samples, and highly sensitive for uninfested samples (Biancolillo *et al*., 2019). The Fourier transform near-infrared (FT-NIR) method was employed to identify infested maize kernels with an accuracy of 86.70% on the basis of distinct wavelengths ranging from 1466 to 2384 nm (Chu *et al*., 2014). This technique is used for detecting both internal and external pest infestations (Mishra *et al.*, 2018). The NIR system has been proven to be faster (< 1-min sample), and is easily adaptable for automated processes, offering a more advanced sampling protocol, especially for large flour quantities. The NIR technique is highly sensitive to the moisture content present in a sample (McClure, 2003). This method is not applicable for detecting the minimum levels of infestation in large samples, and it is unable to differentiate between live and dead insects (Ahmad *et al*., 2018).

Detection of insects by imaging methods

X-ray imaging

X-ray imaging is a non-destructive method for the detection and identification of stored grain insects. Dual-energy X-rays, in particular, have demonstrated efficacy in revealing concealed eggs of stored-product insect pests (Shah and Khan, 2014). X-ray methods are employed for identifying insect pests in diverse agricultural products, including grains, fruits, and vegetables. Soft X-ray imaging serves as an important component in the quality monitoring of stored food grains, and enables the identification of insect infestations at various stages of development (Chuang *et al*., 2011). By providing a clear view of the internal structures of grains, this technique aids in assessing the extent of damage caused by insects without compromising the integrity of the samples. The X-ray method can identify various developmental stages, such as immature stages that feed inside the grain kernels when infestation is substantial (Karunakaran *et al*., 2003a). Both dead and live insects can be detected *via* this method (Rajendran, 2005). In cases of widespread infestation where adult insects are actively moving within a grain sample, it becomes possible to detect adults on the kernels (Table 1).

An X-ray unit was utilised for real-time imaging of wheat kernels by Sharifi and Mills (1971). The selection of kernels depends on the size of the larvae (lesser grain borers) present. The infected kernels were then categorised into three sizes: small, medium, and large. Small larvae covered approximately 10% of the kernels in 2-D view, indicating the infant stages. The medium-stage larvae, corresponding to the immature stage (3rd and 4th instars), occupied a space ranging from 10 to 25% of the kernel in 2-D view. Large-sized larvae, representing the late instar or pupal stage, cover more than 25% of the kernel in 2-D view (Sharifi and Mills, 1971). Fornal *et al*. (2007) developed an algorithm to identify the eggs of *S. granarius* (L.) in wheat grain kernels *via* a soft X-ray imaging technique.

The application of X-ray imaging in stored grain facilities enhances the ability to implement timely and targeted pest control measures. This proactive approach, enabled by accurate and non-destructive imaging, helps mitigate the risks associated with insect infestations, ensuring the preservation of grain quality and minimising economic losses.

Detection of insects via electromagnetic waves

Microwave resonator

This is a technique using a microwave device that is capable of identifying even a single insect in the sample. Microwave resonators operate on the basis of the principles of electromagnetic wave propagation and resonance. Resonance occurs when the frequency of an external electromagnetic field matches the natural frequency of the resonator. This leads to a significant increase in energy absorption, and efficient energy transfer between the external field and the resonator. This microwave resonator consists of a Peltier cell enabling temperature control, a planar microwave resonator that is connected to an external power source, and an insect cage. The measurement techniques include (a) transmission and reflection lines, (b) open-ended coaxial probes, and (c) free space (Alahnomi *et al*., 2021). This device is designed with high sensitivity. This enabled the characterisation of individual insect activity, specifically for pests such as *T. castaneum* or *Cryptolestes ferrugineus*. The detection of adult movements for a single or group of *Oryzaephilus. surinamensis* (L.), *T. castaneum*, and *Lasioderma serricorne* (Brahm) was performed *via* this technique. An existing challenge in this application is the potential uncertainties in sensor signals, which are influenced by various factors, such as location, insect size, and movement speed on the response (Reimer *et al*., 2018). This method is also employed in food processing to ensure food safety and quality. The microwave detection technique holds promise for utilisation in management programs and the non-destructive identification of emerging insect infestations, which would be advantageous for both producers and consumers (Mankin, 2004). Another obstacle closely linked to the utilisation of the food industry is the moisture level, which affects the quality of products in diverse ways. Some products become susceptible to fungal, bacterial, and pest contamination, whereas others undergo improper processing due to unfavourable high moisture conditions. This ultimately diminishes the quality, effectiveness, and shelf life of food items, pharmaceuticals, and chemicals, posing a considerable risk of food poisoning. Additionally, the originality of food composition is widely recognised as a crucial factor (De los Reyes *et al*., 2007).

A current challenge of this application is the possible ambiguities in sensor signals that result from the dependence of the response on insect size, location, and movement speed. One way to circumvent this is the use of an array of sensors that sink into grain bulks to increase the reliability of detection. The sensor could also be used to quickly test insects in grain samples pulled from a grain bulk. In addition to agriculture and food production, the material penetrating ability of the sensor would make it a useful tool for the detection of household pests such as termites, ants, or rodents (Reimer *et al*., 2018).

Table 1. Identification of pests *via* X-ray imaging.

Host	Pest	X-ray model	Stage identified	Classifier	Accuracy	Reference
Wheat kernel	*C. ferrungineus* (S.), *T. casteneum* (H.), *Rhyzopertha dominica* (S.), *Plodia interpunctella* (H.)	LX- 8508, Lixi Inc., Downers, Grove, IL	Eggs, immature, and adult stages	Linear and quadratic function parameter	> 96%	Karunakaran *et al*. (2003b)
	Granary weevil, *S. granarius* (L.)	OEG50, Varian Industries, Salt Lake City, Utah	Eggs and advanced stages	GLM	98%	Haff and Slaughter (2004)
	Lesser grain borer, *Rhyzopertha dominica* (S.)	LX- 8508, Lixi Inc., Downers, Grove, IL	Immature and adult stages	LDA, QDA	98%	Karunakaran *et al*. (2004a)
	Granary weevil, *Sitophilus granarius* (L.)	Elektronika, 25, ARI St. Petersburg, Russia	Eggs and internal stages	LDA	90%	Fornal *et al*. (2007)
	Sitotroga cerealella (Oliver)	Faxitron X-ray digital model, MX-20 DC 12	Gallery, egg, pupae, uninfested seeds	GLM	-	França-Silva *et al*. (2020)
Stored date	Saw toothed weevil, *Oryzaephilus surinamensis* (L.)	Digital Diagonst TH, Philips Medical System, Holanda, Holland, Netherlands	Egg, larvae, pupa, and adult	LDA, SDA	97%	Al-Mezeini *et al*. (2016)

LDA: linear discriminative analysis; SDA: stepwise discriminative analysis; DIA: digital image analysis; and GLM: general linear model.

Conductance-based detection of insects

Conductive roller mill

The conductive roller mill works on the principle of electrical conductance and compression force to detect infestations in stored food products. The existence of adult insects within the kernel leads to an increase in the kernel moisture content, facilitating the differentiation between healthy and infested kernels. This method is not effective for identifying immature stages or insects in grains with low moisture levels (Pearson and Brabec, 2007). The electrical conductive roller mill referred to as an "insect-o-graph" was developed by Pearson *et al.* (2003). Infested and uninfested grain samples were differentiated on the basis of the characterisation of the signals.

A modified conductance mill has been used to detect the immature stages of lesser grain borer infestations in wheat and brown rice. Within 150 s, the modified conductance mill detected 97% large, 83% medium, and 42% small lesser grain borer larvae in 500 g sample of wheat and brown rice. The detection period was greater in wheat than in brown rice (Brabec *et al.*, 2012).

An infestation of the maize weevil, *S. zeamais* was detected at various developmental stages within popcorn kernels *via* a conductive roller mill. They conducted tests with two mills, and reported that the slow-feeding mill successfully detected 91% of medium-sized larvae, 47% of small-sized larvae, and 81% of pupae, whereas the faster mill detected 75% of pupae, 80% of medium-sized larvae, and 43% of small-sized larvae; this method is effective for identifying the immature stages of insect pests (Brabec *et al.*, 2017).

The infested and uninfested kernels were distinguished on the basis of the conductance and the system's received signal. The detection of grains infested with large larvae of *R. dominica*, with an accuracy of 80% in barley and wheat, has been reported. Barley seeds infested with medium-sized larvae were detected at a lower rate than were wheat seeds, *i.e.*, 40% for barley and 65% for wheat. The feeding rate of barley grain samples was lower than that of wheat samples, and the resulting barley sample contained a maximum quantity of larger-sized particles (Brabec *et al.*, 2023).

Although this method is inexpensive, inspecting single grain kernels is time consuming. Kernels infested with insect eggs and young larvae may get undetected because of their low moisture content. Another disadvantage of this method is that it is not useful in detecting kernels with dead internal insects. The rate of insect detection in this method is very low compared with those of inspection by soft X-rays (Pearson *et al.*, 2003).

Detection of insects via antigens or proteins

Enzyme-linked immuno-sorbent assay (ELISA)

ELISA is a sensitive and specific method for detecting and quantifying insect infestations, and associated proteins or antigens in stored grains. It has wider application as a detection tool in quality inspections in the food industry, medicine, *etc*. (Sun *et al*., 2015). Its versatility, sensitivity, and ability to provide quantitative data make it an essential component of stored insect infestation detection. Regular monitoring *via* ELISA ensures timely intervention, and facilitates the development of sustainable practices for stored grain protection. ELISA provides a sensitive and specific method for detecting and quantifying the presence of specific insects and their associated proteins or antigens in stored grains. ELISA involves the use of antibodies that selectively bind to target proteins or antigens. An immunoassay method for detecting insect pest contamination in agricultural commodities was first suggested by Johnson *et al*. (1973). Double immune osmophoresis and immunodiffusion were developed for detecting *S. granarius* in wheat (Rotundo *et al*., 2000). *Rhyzopertha dominica* eggs were detected in the wheat kernels, and myosin was quantified *via* the ELISA method, which is designed specifically for this protein. The degradation of myosin was most rapid within two weeks, with an approximately 58.4% reduction. The described method involves a sandwich ELISA employing monoclonal antibodies (MAbs) directed against species-specific antigens, and polyclonal antibodies (PAbs) generated against identical antigens, which are secondary enzyme-conjugated antibodies, where ELISA has been demonstrated to be effective in identifying the percentage of infestation attributed to the granary weevil *S. granarius* in wheat with diverse insect population densities (Chen and Kitto, 1993). These findings suggest that *Trogoderma granarium*-specific ELISA can be used for the identification of other *Trogoderma* spp. Identification and scoring of several hundred insects is possible within a day due to its high accuracy. The myosin concentrations of *R. dominica* were measured *via* a commercial ELISA (Atui *et al*., 2007). There has been a general agreement of data obtained by immunoassays and the fragment count method, except at very low levels of infestation. Although the method is indirect, it is quantitative, reproducible, and relatively fast (Quinn *et al*., 1992).

Advanced methods for detection of stored grain pests

Acoustic detection

Acoustic detection is a non-destructive method used in the detection of both internal and external feeders in grain masses. The movement and nibbling sounds of insects can be acoustically detected by amplification and filtering. These acoustic sensors can be used to detect either acoustic or mechanical waves. The characteristics of the material or item and any obstacles affect the acoustic wave as it travels through it (Mankin *et al*., 2021; Lutz and Coradi, 2022). As a result, the velocity or amplitude of the acoustic wave is reduced, and the transducers transform these changes into digital or analogue signals (Figure 1).

Typically, a piezoelectric substrate has been used as a sensor for the identification of hidden insect nibbling and crawling sounds within grain kernels after passing through the amplifier and filter chamber. The applications of acoustic devices have been limited by the targeted sounds from background sounds and by the limiting parameters, which include the sound-noise ratio, sensor sensitivity, and sensor range. The effectiveness of acoustic devices in identifying hidden insects relies on various elements, such as the type of sensor used and the range of frequency of the sensor, the size of the insect, the connection between the sensor and the substrate, the temperature, the type of insect detected, the developmental stage, the duration of the assessment, the size and behaviour of the insect, and the distance between the sensors and insects (Mankin *et al*., 2011). The crawling and feeding activities of stored-grain insect pests, *viz.*, *Stegobium paniceum* (L.), *S. oryzae,* and *T. castaneum* were assessed separately *via* piezoelectric sensors, infrared sensors, and microphones in small storage. Acoustic and vibration sensors detect 3 - 10 milli-second signals from three test insects, and have reported that the impulses detected by such economical sensors can be used to detect targeted storage insects (Mankin *et al.*, 2021). A low-cost acoustic insect detection method for *S. oryzae* incidence was detected at a population density of 1.9 adults/kg, and for *T. castaneum,* it was detected at 3.8 adults/kg in 2.6 kg bags at the laboratory level (Mankin *et al.,* 2020).

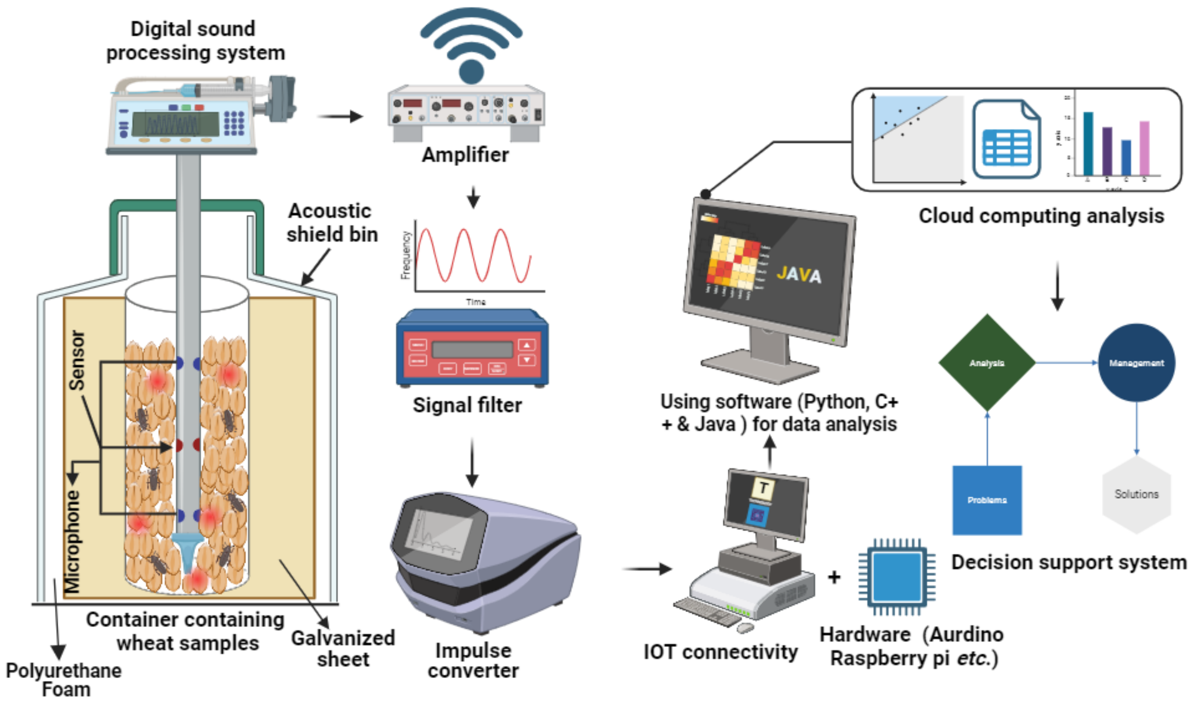

Figure 1. Illustration of acoustic sensor and signal processing system designed for detecting stored-grain insect pest infestation.

The use of modified sensors and software tools for signal processing has made it possible to be more responsive to technological advancements. Spectral and temporal pattern elements are also helpful in differentiating targeted sound and background noise. The sounds of insects are separated from background noise *via* common speech recognition techniques such as hidden Markov models and Gaussian mixture models (Mankin *et al*., 2009). Acoustic tools, along with physical monitoring and pitfall traps, can aid warehouse owners in locating incidences in the storage arena, assisting them in taking measures to reduce losses during storage (Njoroge *et al.*, 2019).

The impulse rate which is the number of impulses per unit time has effectively been used to identify infestations, distinguish species and life stages, and overcome the influence of noise. The burst can range from 50 to 200 impulses (Mankin, 2011) and last from 3 to 30 ms (Mankin *et al*., 2011). Adult lesser grain borers, *R. dominica,* and red flour beetles, *T. castaneum*, produce 37 and 80 times more sound than their larvae do (Mankin *et al*., 2011). Larger amounts of impulses could be used as indicators of higher infestation and increased in number of insects. Background noise tends to be continuous or with isolated pulses, which can be filtered out by setting a threshold for the number of impulses per unit time (Mankin *et al*., 2021).

The acoustic emission consulting AED 2010 L is a portable, battery-operated system with a piezoelectric sensor mounted on a metal probe that is inserted into a grain sample. It was able to detect even one or two insects per kg of wheat grain with 72 to 100% accuracy, and was able to predict the population densities of the tested live samples, including the rice weevil, *S. oryzae*, the lesser grain borer, *R. dominica*, the confused flour beetle, *T. confusum*, the saw-toothed grain beetle, *O. surinamensis*, the rusty grain beetle, *C. ferrugineus*, the khapra beetle, *T. granarium*, and the cigarette beetle, *L. serricorne*, through chi-square tests and machine learning classifiers (Eliopoulos *et al*., 2015; 2016).

The acoustic location fixing insect detector (ALFID) system is designed with a vertical orientation, allowing grains to be loaded and unloaded by gravity. It utilises 16 piezoelectric acoustic sensors arranged in a linear configuration to detect the number of feeding larvae and pinpoint their location within the sample. The sensor signals are amplified by 80 dB, and processed through a bandpass filter ranging from 1,000 to 10,000 Hz. Amplitude threshold detection is used to determine the signal's arrival time, whereas a detection order algorithm calculates the location. The system was tested with up to three rice weevil larvae, *S. oryzae* per kg of wheat, achieving a detection accuracy of 64% with an 8% false positive rate.

These methods lack realistic grain backgrounds, and fail to monitor granary surfaces comprehensively. The automated system combines YOLOv4 and a mobile vehicle with a camera used for pest detection, and achieves 97.55% accuracy. The system enables precise, labour-free pest monitoring, and early warning in grain storage (Chen *et al*., 2022). The crawling and feeding behaviour of bruchids*, viz*., *C. maculatus* and *C. chinensis*, were assessed by placing the acoustic detection probe in a sound-insulated bin in chickpea and green gram. The sounds detected were screened and examined *via* sound analysis software. The amplitudes of *C. chinensis* in chickpea and green grams were measured at 79.32 and 84.01 dB, respectively, for a 59 ms duration, whereas for a 68 ms duration, the amplitude of *C. maculatus* was 97.65 dB in chickpea, and 95.53 dB in green grams at the 300 mm omnidirectional detection range of the sensor (Banga *et al.,* 2019).

In sub-Saharan Africa, an acoustic device was developed for the detection of *Prostephanus truncates* and *S. zeamais* in maize (Kiobia *et al*., 2015). The sensors could detect larval impulses up to a distance of 25 cm, and software devices were developed on the basis of observations and variations in the temporal and spectral patterns of insect noise correlated with variations in physiological activity. It is expected that acoustic detection technology will continue to advance, making automation easier and minimising the expense of detecting stored-product insects. In recent years, insect acoustic trapping has also been used as an advanced non-destructive detection technique. This could be because accurate estimations of infestation density require large numbers of samples, and result in greater deviations in the rates of sound generated by individual insects, especially in immature stages (Eliopoulos *et al*., 2015; 2016; Njoroge *et al*., 2019; Mankin *et al*., 2020).

Machine learning (ML) algorithms have been applied to improve the accuracy of acoustic insect detection. Although raw acoustic data can be fed directly into training algorithms, the data are often pre-processed to extract features such as Mel-frequency cepstral coefficients (MFCCs), spectral centroid, spectral flatness, spectral roll-off, linear predictive cepstral coefficients (LPCCs), and line spectral frequencies (LSFs). The data can also be converted into spectrograms, two-dimensional graphical representations of the magnitude of the signal at various frequencies over time, which can be used with traditional image classification models (Kadyrov *et al*., 2024). ML requires large datasets to train and test models. The Animal Sound Archive, InsectSet32, InsectSet42, InsectSet66, and the Singing Insects of North America, all feature recordings of insects; however, they are not species commonly found infesting stored grains and products. The BugByte sound library is the only publicly available dataset of insect sounds with recordings of stored product pests' movement and feeding in various materials (Mankin, 2019).

Artificial neural networks (ANNs) are computer models of brain neuron linkage processes that combine weighted inputs from observational data, *e.g*., acoustic signal pulses, and produce a single binary output that learns its correct value from the observational inputs *via* backpropagation or other methods. Machine learning methods incorporate neural networks, including convolutional neural networks (CNNs), probabilistic neural networks (PNNs), perceptual learning prediction (PLP), decision trees and forests, hidden Markov models (HMMs), support vector machines (SVMs), Bayesian classifiers, and other methods to improve predictions automatically through experience with datasets where the target insect species have been independently identified (Romano *et al*., 2013). Deep learning is a machine learning method that incorporates multiple layers of neural networks, each of which extracts specific features or learned representations of input data (Jordan and Mitchell, 2015).

One of the challenges of using acoustic sensors for detecting insects in stored products is the interference of external noise from the surrounding environment, such as factory machinery, vehicles, wind, and other sources. External noise can mask the low-intensity sounds produced by insect feeding and movement, which typically range from 20 to 80 dB SPL (sound pressure level) at frequencies below 10 kHz. The acoustic detectors were shielded *via* a multi-layered enclosure that attenuated sounds by 70 to 85 dB between 1 and 10 kHz. This method enables reliable detection of internally feeding larvae in grain samples at inspection facilities with high noise backgrounds, and it cannot detect dead insects in grain, as well as infestation, which cannot be detected at early larval stages (Mankin *et al*., 1996). Until now, however, commercial insect detection devices have not yet fully achieved versatility, ease of use, and cost-effectiveness of currently available cell phones, and have not rapidly supplanted pheromone or probe traps, sifting, or other insect pest detection methods in general use. The potential of increased scalability and increased automation nevertheless continues to drive interest from commercial suppliers of insect acoustic detection technology.

Environmental sensing

Environmental sensing is a crucial aspect of modern technology that involves the use of sensors and monitoring devices to gather data about the surrounding environment. These sensors are designed to detect and measure various physical, chemical, and biological parameters, providing valuable insights into environmental conditions. The major ecological factors to be considered for effective grain storage without quality deterioration are moisture content, carbon dioxide, temperature, and oxygen. Temperature, relative humidity, and moisture content play crucial roles in the growth and development of insects (Guru *et al*., 2022). These elements can influence the survival rates of both immature and adult insects, and other microorganisms found in stored grains. Temperature measurements in various storage units can be recorded *via* temperature cables, thermocouples, thermometers, and temperature sensors (Kaushik and Singhai, 2018). Temperature sensors are rapid, low cost, and can be used for precise temperature measurements.

Detecting grain spoilage resulting from moulds, mites, and insects involves measuring the level of CO_2 in the intergranular air. The CO_2 concentration levels fluctuate, and sensors can be used to observe these changes during the respiration of organisms. CO_2 concentrations ranging between 1,100 and 1,500 ppm signal the beginning of mould growth, whereas carbon dioxide concentrations exceeding 1,500 to 4,000 ppm indicate severe mould infection or infestation of stored grains by insects (Gonzales *et al*., 2009) (Table 2).

Table 2. List of sensors used for environmental sensing.

S.no	Sensor	Sensor type	Reference
1.	LM35	Temperature sensor	Maier *et al*. (2006)
2.	DHT22, SHT21, SY-HS-220	Temperature / RH sensor	Maier *et al*. (2006); Singh and Fielke (2017)
3.	Metal oxide sensor (MOS), MQ7	Carbon dioxide sensor	Neethirajan *et al*. (2009)
4.	LM35, SY-HS-220	Temperature / RH sensor	Patil *et al*. (2023)
5.	ISO 6639- 3: 1986	Temperature / RH sensor	Banga *et al*. (2020)
6.	DHT 22 (AM2302, Aosong (Guangzhou) Electronics Co., Ltd.) - 300 mm omnidirectional	Temperature / RH sensor	Banga *et al*. (2019)
7.	SHT75 single module (Sensirion AG, Zurich, Switzerland)	Temperature / RH sensor	Uddin *et al*. (2006)
8.	ESP32	Temperature / RH sensor	Talpur *et al*. (2021)
9.	PABA-Sensor (380 - 2400 ppm of CO_2)	Carbon dioxide sensor (2455 ppm)	Neethirajan *et al*. (2010)
10.	MQ-135	Carbon dioxide sensor	Kodali *et al*. (2020)
11.	DHT-11	Temperature/RH sensor	Kodali *et al*. (2020)

Olfactory-based method of detection

Electronic nose (E-nose)

Electronic nose (E-nose) technology is a sensory system that mimics the human olfactory system for the detection and identification of odours or volatile compounds. E-noses typically use an array of sensors with different sensitivities to various volatile compounds (Figure 2). This array helps capture a broader range of odours, enhancing the system's ability to differentiate between different insect pests or stages of infestation (Hussain *et al*., 2019; Karakaya *et al*., 2020). The E-nose system relies on pattern recognition algorithms to analyse the data generated by the sensor array. Machine learning and statistical methods are commonly employed to train systems to recognise specific patterns associated with different insect pests or infestation levels (Wu *et al*., 2013). The E-nose system should be calibrated with the baseline odour profile of the stored grain without infestation. Stored-grain insect pests release specific volatile compounds during various life stages, such as mating, feeding, and egg laying. E-noses are trained to recognise these unique chemical signatures, allowing for early detection of infestations. As the E-nose sensor array interacts with the stored grain environment, it produces a unique pattern or "smell print" that can be analysed to determine the presence and severity of insect pests. This helps in establishing a reference point and increases the accuracy of pest detection by identifying deviations from the normal odour. Conducting polymers (CPs) and metal oxide semiconductors (MOSs) are the most commonly used sensors, but alternative technologies such as metal oxide semiconductor field-effect transistors (MOSFETs), carbon dioxide (CO_2), optical fibre live cells (OF-LCs), carbon black composites (CBCs), and surface acoustic waves (SAWs) have also been used (Zheng and Zhang, 2022). E-nose-based detection of *R. dominica* infestation in stored food grains was performed with 18 metal oxide E-noses. They reported that the E-nose is applicable for ensuring the high precision of artificial neural networks in ensuring the data analysis of data without any loss of information (Srivastava *et al*., 2019).

E-nose technology can be integrated with other monitoring systems, such as temperature and humidity sensors. Combining multiple data sources enhances the overall understanding of the stored grain environment and provides a more comprehensive pest management strategy. The accurate, rapid and non-destructive detection characteristics of E-noses have great potential for application in the field of grain storage. The limitations of this method include its high cost and high specificity for some groups of insect species (Srivastava *et al*., 2019).

Solid-phase microextraction (SPME) method

Solid-phase microextraction (SPME) is a widely used innovative and efficient detection

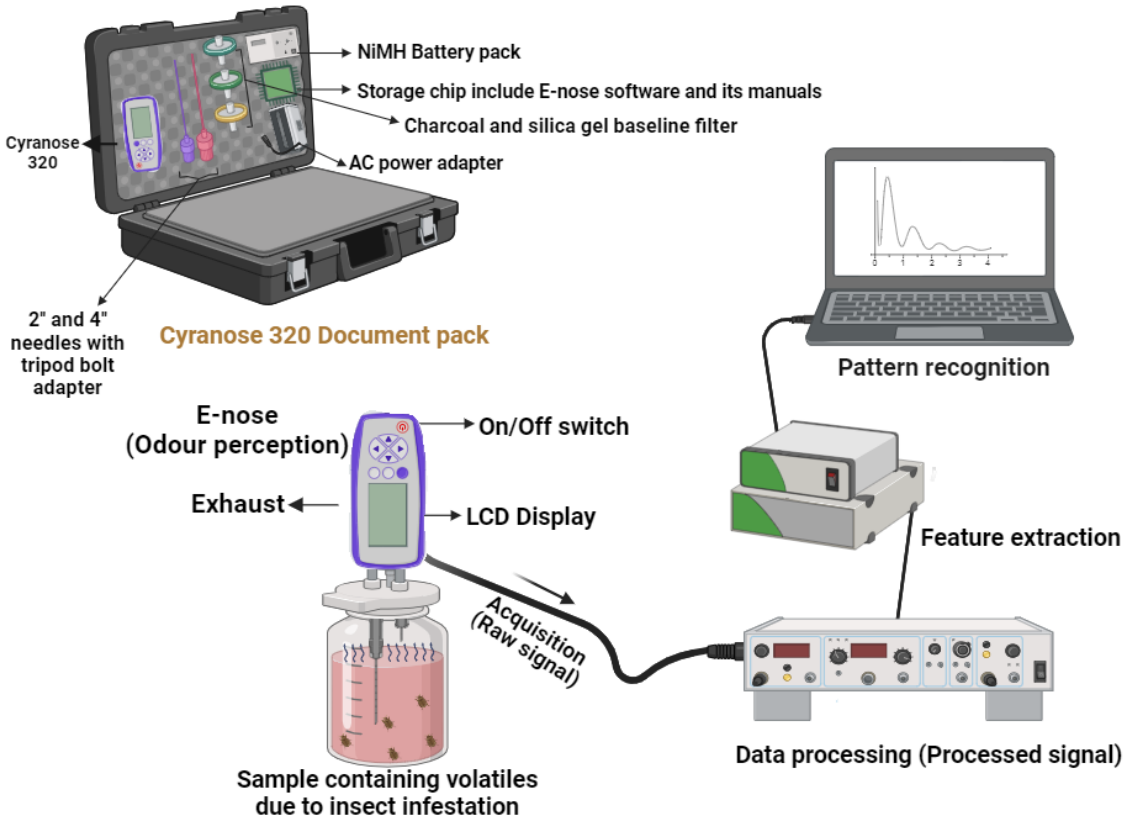

Figure 2. Schematic representation of E-nose setup.

technique gaining prominence in the monitoring and control of stored-grain insect pests. Solid-phase microextraction (SPME) is a simple, sensitive, rapid, and solvent-free technique for the extraction of analytes from gaseous, liquid, and solid samples, and is among the leading microextraction methods. The application of SPME in sample preparation has been increasing continuously over the last decade. It is most often used as an automated fibre injection system coupled with chromatographic separation modules for the extraction of volatile and semi volatile organic compounds, and allows for the trace analysis of compounds in complex matrices. The SPME process is composed of two basic steps: (i) partitioning of analytes between the extraction phase and the sample matrix, and (ii) desorption of concentrated extracts into an analytical instrument (Adahchour *et al*., 2002). SPME offers a sensitive and non-invasive method for the identification and quantification of volatile organic compounds (VOCs) emitted by these pests, enabling early detection and intervention. SPME involves the extraction of target compounds from the headspace of a sample *via* a coated fibre that selectively adsorbs volatile analytes. The fibre is then desorbed in the injection port of a gas chromatograph (GC), allowing for the separation and identification of the compounds of interest. SPME coupled with gas chromatography-mass spectrometry (GC-MS) facilitates the identification and differentiation of various stored-grain insect pests (Cai *et al*., 2022). A relatively small number of *R. dominica* infestations in wheat were detected *via* SPME coupled with GC-MS and GC-FID (Niu *et al*., 2016). Head space SPME coupled with GC-MS was used to determine the correlation between insect infestation and stored grain quality in *T. castaneum* and *C. ferrugineus* (Senthilkumar *et al*., 2012). By using the head space SPME method combined with the GC-MS technique, the characterisation of semiochemicals (SCSs) was adapted for *C. maculatus*, *S. oryzae*, and *T. castaneum*. SPME is environmentally friendly as it minimises the need for chemical solvents and reduces the overall environmental impact of pest monitoring (Lokesh *et al*., 2023). SPME was used to collect volatile organic compounds (VOCs) released by *T. castaneum*. The major components, methyl-1,4-benzoquinone (MBQ), ethyl-1,4-benzoquinone (EBQ), and 1-pentadecene (C15:1) were analysed *via* capillary gas chromatography-mass spectrometry (CGC-MS).

CAR/PDMS fibres captured the highest quinone levels (~75%), outperforming the other fibres. The SPME-CGC method is effective for detecting *T. castaneum* volatiles, aiding in stored product infestation monitoring.

The SPME technique appears to be easy to perform but is sensitive to the time and temperature of extraction. With its application in the detection of insect infestations, further development is needed to improve the sensitivity of the technique to detect insects that produce relatively few pheromones (Laopongsit *et al*., 2014) or other volatiles, especially at very low concentrations. SPME has several advantages over traditional extraction methods. It is not only a rapid, simple, and solvent-free method, but also sensitive and provides linear results for a wide range of concentrations and analytes. In addition to the low concentrations of analytes, quantitative or semiquantitative data are provided, and losses that can occur during the extraction, concentration, and clean-up steps of traditional sample procedures are mostly avoidable (Nerín *et al*., 2009).

One of the main drawbacks of SPME techniques is the limited number of commercially available stationary phases (fibre materials) that only roughly cover the scale of polarity of target analytes. In particular, the extraction of polar analytes from samples with a polar matrix poses a problem (Souza-Silva and Pawliszyn, 2015). Other challenges are the recommended operating temperature (240 - 280°C), instability and swelling in organic solvents, breakage of the fibre, stripping of coatings, bending of the needle, and cost, as well as the limited lifetime of the fibre (Namieśnik *et al*., 2000; Nerín *et al*., 2009). Furthermore, sample carry-over may occur, and high-molecular-weight compounds cannot be analysed in combination with GCs (Namieśnik *et al*., 2000). In certain cases, low extraction efficiencies are reported, particularly in the case of highly volatile, polar, or thermally unstable analytes.

Detection of insects via imaging method

Machine vision

Machine vision systems can detect the presence of insect infestations at an early stage, even before they cause visual damage. Early detection allows prompt intervention and prevention of infestations. Continuous monitoring of storage areas *via* cameras and sensors enables real-time surveillance. Machine vision algorithms analyse images to identify potential signs of insect infestation or unusual behaviour (Park *et al*., 2023). Machine vision systems can be trained to recognise different insect species on the basis of their visual characteristics. By analysing images of stored products, machine vision can assess the damage caused by insects. Computerised image analysis has been shown to have great potential for detecting and identifying various non-grain particles and insects in wheat. A machine vision system for detecting insects in grains consists of a high-speed integrated machine vision software package with a monochrome charge-coupled device (CCD) camera and a personal computer. Machine vision aids in assessing the risk of infestation on the basis of factors such as temperature, humidity, and the type of stored product (Vithu and Moses, 2016), and longwave infrared (LWIR) hyperspectral imaging is used to examine damaged wheat kernels. The wheat kernels affected by the rusty grain beetle, *C. ferrugineus,* rice weevil, *S. oryzae,* red flour beetle, *T. castaneum,* and lesser grain borer, *R. dominica,* were scanned at wavelengths ranging between 1000 and 1600 nm with greater than 90% accuracy *via* structural and colour information (Table 3). The insects and body parts in the bulk wheat samples were detected *via* pattern recognition and multivariate analysis, and more than 90% accuracy was obtained (Zayas and Flinn, 1998).

An insect monitoring system using RGB cameras and YOLO deep-learning models was used to detect and identify six stored product insect species in various environments. A dataset of 2,630 images with 14,509 labelled insects were used to train six YOLO variants, which achieved high detection accuracy (> 76%) and fast inference speeds (12 - 36 ms). The lightweight YOLOv8l model was successfully deployed on mobile devices, offering a cost-effective, accurate, and scalable solution for real-time insect detection in stored product facilities (Badgujar *et al*., 2023).

Different algorithms and improved systems have been developed to achieve high throughput, reduce instrument and computational costs, allow easy data access and real-time monitoring, and cover different insect pest species (Lima *et al*., 2020). A deep neural network was used to detect and identify six species of stored grain insects that were blended with grain and dockage materials (Shen *et al*., 2018). Although they achieved a high mean average precision (mAP) of 88%, they used different models

Table 3. List of infrared sensors and accuracy (%) in machine for stored-product insect pests.

Crop	Type of insect	Type of infrared sensor	Classifier	Model of signal	Accuracy (%)	Reference
Wheat	*Tribolium casteneum, Sitophilus oryzae, Cryptolestes ferrugineus*, *Rhyzopertha dominica*	InGaAs camera	QDA, LDA	Reflectance	> 85	Singh *et al*. (2009)
Wheat	*Sitophilus oryzae, Tribolium casteneum, Rhyzopertha dominica, Cryptolestes ferrugineus*	CCD area scan image sensor, digital camera	QDA, LDA	Reflectance	> 92.7	Singh *et al*. (2010)
Oil palm	*Sitophilus oryzae, Rhyzopertha dominica, Tribolium casteneum, Cryptolestes ferrugineus*	FT-IR	NB, KNN, QDA, and LDA	Reflectance	> 90	Liaghat *et al*. (2014)
Wheat	*Rhyzopertha dominica*	Progress 3000 colour camera (Kontron)	LDA, QDA, and CDA	Reflectance	> 90	Zayas and Flinn (1998)
Sorghum	*Sitophilus zeamais*	FT-NIR	Partial least square analysis, LDA	Reflectance	97.1	Santos *et al*. (2019)
Rice	*Plodia interpunctella*	Nicolet 6700 FT-NIR and InGaAs detector	PLS-DA, SIMCA	Reflectance	97.5	Biancolillo *et al*. (2019)

LDA: linear discriminative analyser; QDA: quadratic discriminative analyser; KNN: nearest neighbour; NB: Naïve Bayes; SIMCA: soft independent modelling of class analogy; and PLS-DA: partial least squares discriminant analysis for different insects, and encountered issues such as one species being classified as two. Another insect detection system built on a deep CNN focused on different insect sizes, and obtained mAPs of up to 95%. However, only one insect species at a time is detected. Some benefits of machine vision include (a) the ability to analyse images and videos much faster and with higher accuracy than humans do, which makes it suitable for high-speed quality control, inspection, and sorting tasks; (b) the ability to perform tasks consistently without errors or fatigue, ensuring consistent results; (c) the ability to analyse images and videos without physical contact, making it suitable for inspecting hazardous or fragile materials; (d) the flexibility of programming machine vision systems to analyse a wide variety of images and videos, enabling them to be used for various applications; and (e) the potential to reduce labour costs and enhance productivity, making it a cost-effective option for many applications. However, the use of machine vision also has several drawbacks, which include (a) the complexity of designing and implementing the systems, which require expertise in both hardware and software; (b) the cost of developing and implementing the systems, especially for specialised applications; (c) the systems' sensitivity to lighting conditions, which can affect the accuracy and consistency of their results; (d) the limited understanding of context and inability to make judgments on the basis of experience or intuition of systems using machine vision; and (e) the limited applicability of the systems, especially for applications that require complex decision-making skills beyond image analysis.

The application of machine vision in storage entomology involves leveraging visual data and advanced algorithms to monitor, detect, and manage insect-related risks in storage environments. A major obstacle to the development of commercially useful machine vision systems for insect detection in grain is the limited rate of sample throughput. Simple, fast, and reliable algorithms are needed to inspect a statistically significant portion of a grain sample in a short term. Furthermore, device complexity, particularly in terms of camera type, computer specifications, and sample delivery system must be minimised to make this approach cost effective. Another disadvantage is that it can detect only external insects in grain bulks, whereas NIR spectroscopy and X-ray methods can detect internal insects (Neethirajan *et al*., 2010).

Thermal imaging

Thermal imaging technology has emerged as a valuable tool in various fields, including agriculture and pest management. This non-invasive and non-destructive technology uses infrared radiation to detect temperature differences on surfaces, enabling the identification of potential pest infestations (Al-Doski *et al*., 2016). The thermal imaging technique holds significant promise in identifying various postembryonic stages of insects through temperature variations and heat generated through insect respiration (Nanje Gowda and Alagusundaram, 2013).

Thermal imaging in insects is based on the principle of detecting infrared radiation emitted by the insect's body. Infrared radiation constitutes a form of electromagnetic radiation characterised by wavelengths longer than those of visible light. The principle of thermal imaging in insects involves the following key aspects: Infrared radiation emission and objects that possess a temperature higher than absolute zero emit infrared radiation. The amount of radiation emitted is directly related to the insect's temperature. In thermal imaging, sensors are used to detect this emitted infrared radiation. With respect to temperature variation, insects have different body temperatures depending on their activity, environmental conditions, and physiological state (Lazzari, 2019).

For example, a flying insect may have a higher body temperature due to increased muscle activity. Thermal imaging allows visualisation of these temperature variations. Thermal cameras or sensors are used to capture the infrared radiation emitted by insects. These sensors are designed to detect and convert infrared radiation into visible images or data that represent temperature differences. The resulting thermal image provides a temperature map of the insect and its surroundings. In thermal imaging, diverse hues or tones are frequently employed to depict different temperature gradients. Regions with higher temperatures are depicted with brighter or warmer colours, such as red or yellow, whereas regions with lower temperatures are depicted with darker or cooler colours, such as blue or purple. This colour mapping helps in interpreting the thermal patterns of insects (Nguyen *et al*., 2021). Wheat kernels infested by the rusty beetle *C. ferrugineus* were detected *via* a thermal camera 50, with an accuracy of 83.5% (Manickavasagan *et al*., 2008). The egg, larval, and pupal stages of the pulse beetle

C. maculatus were identified *via* a thermal camera with an accuracy of 83% (Chelladurai *et al*., 2012).

Thermal imaging in insects relies on detecting infrared radiation emitted by the insect's body to create a visual representation of temperature variations. This technology provides valuable insights into insect biology, behaviour, and environmental interactions. The integration of thermal imaging into pest control strategies is likely to become even more prevalent, contributing to a greener and more efficient approach to pest management. Thermal imaging is an expensive system with a cost-prohibitive system and camera price; thus, its application is limited to only laboratory settings and high-value target analyses.

Conclusion

The detection of stored-grain insect pests is critical for safeguarding global food security, and preserving economic stability in the agricultural and food industries. The present review underscores the importance of advanced and improved methods for the early detection of stored-grain pests. While these techniques have demonstrated their potentials to mitigate postharvest losses and ensure food security, there is room for further research to enhance their efficacy. Future studies should focus on integration of advanced technologies for the development of low-cost, portable, and user-friendly devices; incorporating AI, machine learning, and IoT capabilities which can enhance real-time pest detection and decision-making processes, field validation, and scalability for comprehensive field studies across diverse geographical and environmental conditions, which are required to validate the performance of these techniques. Emphasis should also be placed on scalability and accessibility for smallholder farmers and sustainability, and environmental impact for future research should focus on creating eco-friendly detection methods with minimal environmental footprint, ensuring compliance with global sustainability goals, and data standardisation and sharing to establish the standardised protocols for data collection, analysis, and sharing across platforms which can enable collaborative research and improve the reliability of pest detection systems. Public-private partnerships to encourage the collaboration between academia, industry, and policymakers can accelerate the adoption of innovative pest detection technologies and drive investment in this critical area. By addressing these areas, future research can overcome existing limitations, foster widespread adoption of advanced pest detection methods, and significantly reduce postharvest losses, thereby contributing to global food security.

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