AgriBio Innovations
(Published by Research Trend, Website: www.agribioinnovations.com)
ISSN NO. (Online): 3049-3862
Volume-2, Issue-1, Jan.-Dec., 2025 2(1): 31-43(2025)

Advancements in Electronic Nose Technology for the Detection, Identification, and Monitoring of Insect Infestation in Stored Agricultural Grains: A Comprehensive Review

Merve Elçiçek[1*], Doğan Ergün[1], Bashir Ahmad Sheikh[2] and Ayşegül Esra Gölcü[3]
[1]University of Cukurova, Biotechnology Department, Balcalı Adana Turkey.
[2]Department of Zoology, S.P. College Cluster University Srinagar India.
[3]Department of Horticulture, Faculty of Agriculture, Cukurova University, Adana, Turkiye.
(Corresponding author: Merve Elçiçek)*
(Received: 22 January 2025; Revised: 18 March 2025; Accepted: 02 April 2025; Published: 17 April 2025)
(Published by Research Trend)
DOI: https://doi.org/10.65041/abi.15

ABSTRACT: With yearly economic losses estimated at billions of dollars, post-harvest losses from insect pest infestations in stored grains pose a serious threat to global food security. Visual examination, trapping methods, and chemical analysis are the mainstays of traditional pest detection methods in grain storage facilities. These approaches are often labour-intensive, time-consuming, and may not identify infestations in their early stages. A possible non-destructive, quick, and affordable substitute for detecting, identifying, and tracking grain pest infestations is electronic nose (e-nose) technology. Examining the fundamental ideas, sensor technology, pattern recognition algorithms, and field applications, this review summarises recent studies on e-nose uses in agricultural grain pest control. We examine the performance attributes of several e-nose systems, talk about their drawbacks and restrictions, and provide suggestions for future lines of inquiry. *Sitophilus species*, *Rhyzopertha dominica*, *Tribolium species,* and *Oryzaephilus surinamensis* are among the major grain storage pests covered in the review. It emphasises how electronic nose technology can be used to detect volatile organic compounds (VOCs) released by these pests and damaged grains. Some methods may identify infestations at population densities as low as 1–5 insects per kilogramme of grain, according to current research, which shows detection accuracies for a variety of pest species ranging from 80–95%. For broad commercial usage, however, issues with standardisation, environmental interference, and long-term sensor stability still need to be resolved.

Keywords: Electronic nose, grain storage, pest detection, volatile organic compounds, pattern recognition, food security.

INTRODUCTION

Population increase, climate change, and post-harvest losses are all putting increasing strain on global food security, and one of the biggest problems in the food supply chain is insect infestations in stored grains. According to the Food and Agriculture Organisation (FAO), insect pest-related post-harvest losses make up 10–40% of the world's grain output, resulting in yearly losses of more than $5 billion (Phillips & Throne, 2010). Although industrialised nations also have significant difficulties in preserving grain quality during storage, these losses are more severe in poor nations due to a lack of storage facilities and pest control skills (Hagstrum & Subramanyam 2006).

In grain storage facilities, visual examination, pitfall traps, probe traps, and chemical residue analysis are the mainstays of traditional pest detection techniques. Despite being the norm for many years, these techniques have built-in drawbacks that reduce their usefulness in contemporary grain storage operations. Visual examination is subjective, time-consuming, and often misses early-stage infestations when remediation would be most successful. It also needs skilled staff (Trematerra & Sciarretta 2004). Although trapping techniques are helpful for monitoring, they are not very good for early warning systems since they usually discover pests only after populations have developed (Toews *et al.,* 2006). Despite their accuracy, chemical analysis techniques are not feasible for regular monitoring applications because they need laboratory space, skilled staff, and a substantial amount of time for sample preparation and analysis (White *et al*., 1990).

Grain pest monitoring and detection have undergone a paradigm change with the advent of electronic nose (e-nose) technology. By detecting and identifying volatile organic compounds (VOCs) in the air space above samples, electronic noses are analytical tools that are intended to replicate the human olfactory system (Gardner & Bartlett 1994). According to Paolesse *et al.* (2006), the basic idea behind e-nose applications in grain pest detection is that grains afflicted with insects release distinct patterns of volatile chemicals that are different from those produced by uninfested grains. According to Chambers *et al.* (2013), these volatiles include molecules released from damaged grain kernels, metabolites produced by the insects themselves, and secondary metabolites from fungal contamination, which often coexists with insect infestations.

E-nose technology has a lot of potential benefits for detecting grain pests. Electronic noses are appropriate for continuous monitoring applications because they provide quick, non-destructive examination with little sample preparation needed (Pearce *et al*., 2003). Unlike conventional techniques, the technology may be able to identify infestations at lower population densities, allowing for earlier intervention and a decrease in the requirement for chemical treatments (Wilson & Baietto 2009). Grain handling operations may also benefit from the automation and integration of e-nose systems, which lowers labour costs and produces quantifiable, objective findings that are less reliant on operator skill (Turner & Magan 2004).

Nevertheless, there are particular difficulties in using e-nose technology for grain pest identification. Variable temperature, humidity, and airflow conditions are characteristics of grain storage settings that might impact volatile emission patterns and insect metabolism (Paolesse *et al.,* 2006). Sophisticated pattern recognition algorithms and reliable sensor systems are required to handle the complex analytical challenges posed by the presence of numerous pest species, different grain types and conditions, and possible interference from other sources of volatiles in storage facilities (Wilson & Baietto 2011).

With the advances in recent technologies, Smart farming allows to utilize Internet of things (IoT) to assist the farmers for reducing the wastages and improving the productivity (Sindhu and Indirani 2020). Sensors, drones, and precision farming software especially artificial intelligence and machine learning are rapidly being used in agriculture to increase efficiency, production, and sustainability (Lingireddy *et al*., 2023).

Zero Budget Natural Farming (ZBNF) is a technique for chemical-free agriculture that is based on traditions from ancient India (Mohammed Ghouse *et al*., 2025).

This study offers a thorough examination of recent studies on the use of electronic noses for agricultural grain pest identification, monitoring, and detection. We look at the scientific underpinnings of these applications, assess how well different e-nose systems and sensor technologies work, study data processing and pattern recognition strategies, and talk about real-world implementation issues for commercial grain storage operations. Along with discussing present restrictions and difficulties, the paper offers suggestions for future lines of inquiry that can improve the efficiency and use of e-nose technology in grain pest control.

PRINCIPLES OF ELECTRONIC NOSE TECHNOLOGY FOR PEST DETECTION

Using arrays of chemical sensors and sophisticated signal processing algorithms, electronic nose systems replicate the function of biological olfactory systems by operating on the basis of pattern recognition of volatile organic compound signatures (Gardner & Bartlett 1994). The basic idea behind e-nose applications in grain pest identification is that, by using multivariate analysis of sensor responses, insect-infested grains may be identified from uninfested samples by their distinctive patterns of volatile chemicals (Paolesse *et al.,* 2006; Sri *et al*., 2021; Kumar 2023; Bais *et al*., 2023; Prashanth Kumar 2023; Saleem *et al*., 2021).

The grain-pest ecology has a variety of sources for the volatile organic molecules that are important for detecting grain pests. Direct metabolites generated by insect pests during eating, breathing, and reproduction are examples of primary sources (Chambers *et al*., 2013). As they feed grain endosperm and mature, Sitophilus species—also referred to as grain weevils—produce unique patterns of aldehydes, alcohols, and esters (Phillips *et al*., 1993). Because of their feeding habits and the mechanical harm they inflict on grain kernels, Rhyzopertha dominica (lesser grain borer) infestations are characterised by the formation of certain terpene chemicals and oxidised fatty acid derivatives (Germinara *et al.,* 2007).

Compounds emitted from damaged grain kernels as a consequence of insect feeding activities are examples of secondary volatile sources. According to Chambers *et al*. (2013), chewing insects create mechanical damage that upsets cellular architecture and enzymatic functions, causing previously compartmentalised chemicals to leak out and new volatiles to arise via oxidation and degradation processes. Even while insect-specific metabolites may be present in trace amounts, these damage-associated volatiles often contain lipid oxidation products as hexanal, pentanal, and different ketones, which act as indirect markers of pest presence (White *et al*., 1995).

Compounds generated by fungal contamination, which often coexists with insect infestations, are classified as tertiary volatile sources. Many stored grain pests promote circumstances conducive for fungal development by the entrance of moisture and the production of micro-wounds in grain kernels (Sinha & Muir, 1973). Additional indicators of storage degradation linked to pest activity may be found in the distinctive patterns of alcohols, ketones, and sesquiterpenes produced by fungi such Aspergillus and Penicillium species (Magan & Evans 2000).

The concentration and volatility of target chemicals in the headspace above grain samples have a significant impact on the e-nose systems' sensitivity of detection. Temperature, humidity, feeding activity, grain type and condition, developmental stage, and pest population density are some of the variables that affect volatile emission rates (Wilson & Baietto 2009). Early-stage infestations may produce lower concentrations of target compounds but may also display more specific chemical signatures because secondary effects are less complex, according to research showing that volatile emission patterns change dynamically as infestations progress (Chambers *et al.,* 2013).

An essential part of efficient e-nose systems for grain pest detection is sensor array design. Metal oxide semiconductors (MOS), conducting polymers, quartz crystal microbalances (QCM), and surface acoustic wave (SAW) sensors are the most widely used sensor technologies. Each has unique benefits and drawbacks for grain storage applications (Pearce *et al.,* 2003). High sensitivity to reducing gases is a feature of metal oxide semiconductor sensors, which are especially useful for identifying alcohols and aldehydes that are often linked to grain degradation (Persaud & Dodd 1982). Conducting polymer sensors are useful for identifying metabolites unique to insects because they have a high sensitivity to organic vapours and may be configured to react only to certain classes of compounds (Gardner & Bartlett 1994).

Target volatile compounds' chemical variety must be carefully taken into account while optimising the composition of sensor arrays while preserving an acceptable level of data complexity for pattern recognition algorithms. According to research, arrays including six to twelve sensors with complimentary response characteristics may reliably distinguish between grain samples that are infected and those that are not, all the while offering enough redundancy to guarantee dependable operation (Wilson & Baietto 2011). Cross-reactive sensor arrays, where individual sensors respond to various compound classes, have proved especially successful for grain pest detection applications since they capture the complexity of volatile emission patterns while preserving realistic system designs (Turner & Magan 2004).

In order to convert intricate sensor response patterns into useful pest detection data, pattern recognition algorithms are essential. In order to visualise sample clustering and identify important factors that contribute to discriminating between infested and uninfested samples, principal component analysis (PCA) has been used extensively for preliminary data exploration and dimensionality reduction (Jolliffe, 2002). With stated accuracies of over 90% for differentiating between pest species and infestation levels, linear discriminant analysis (LDA) and partial least squares discriminant analysis (PLS-DA) have shown exceptional performance for classification tasks (Balasubramanian *et al.,* 2007).

For complex pattern recognition tasks involving multiple pest species and varying environmental conditions, advanced machine learning techniques such as support vector machines (SVM), random forest algorithms, and artificial neural networks (ANN) have shown superior performance (Loutfi *et al.,* 2015).

These algorithms provide strong performance even when there is environmental unpredictability and sensor drift, and they can manage non-linear correlations between sensor responses and pest traits (Wilson & Baietto 2009).

For e-nose applications in grain pest monitoring, the temporal dynamics of volatile emission patterns provide both potential and constraints. Studies have shown that as infestations spread, volatile emission profiles alter dramatically, necessitating the use of temporal pattern recognition algorithms and dynamic calibration techniques (Chambers *et al*., 2013). Nevertheless, these temporal patterns also provide useful data for determining the age and severity of infestations, which may allow for more complex pest management choices based on population growth prediction models (Phillips & Throne 2010).

SENSOR TECHNOLOGIES AND SYSTEM DESIGN

The efficacy and dependability of electronic nose systems for grain pest detection applications are largely determined by the choice and refinement of sensor technology. Several sensor systems have been assessed in recent studies, and each offers unique benefits for identifying the wide variety of volatile organic chemicals linked to infestations of pests in grain storage (Wilson & Baietto 2009).

Because of its high sensitivity, wide dynamic range, and affordable price, metal oxide semiconductor (MOS) sensors have become one of the most researched technologies for grain pest detection (Persaud & Dodd 1982). When target gas molecules come into contact with a heated metal oxide surface, usually tungsten oxide (WO_3) or tin oxide (SnO_2), these sensors work by altering electrical conductivity (Gardner & Bartlett 1994). Under controlled laboratory circumstances, research by Balasubramanian *et al*. (2007) showed that MOS sensor arrays could successfully differentiate between grain samples infested with Sitophilus oryzae, Rhyzopertha dominica, and Tribolium castaneum with classification accuracies above 92%. One of MOS sensors' main benefits is its remarkable sensitivity to reducing gases, such alcohols and aldehydes, which are common constituents of volatile emissions from insect metabolites and damaged grains (Chambers *et al.,* 2013). Furthermore, when run at constant temperatures, MOS sensors show high stability and repeatability, which qualifies them for automated monitoring applications (Pearce *et al*., 2003). Nevertheless, these sensors also have drawbacks, such as high power consumption because of heating needs, possible sensitivity to changes in ambient humidity, and vulnerability to toxicity from sulfur-containing substances that could exist in grain storage settings (Turner & Magan 2004).

Another significant technological platform that has shown encouraging outcomes for grain pest detection applications is conducting polymer sensors. Excellent sensitivity to a variety of organic vapours is provided by these sensors, which function by altering electrical characteristics when volatile organic chemicals contact with specialised polymer films (Gardner & Bartlett 1994). Research by Paolesse *et al.* (2006) demonstrated that conducting polymer sensor arrays could detect Sitophilus infestations in wheat samples at population densities as low as 2-3 insects per kilogram of grain, representing a significant improvement in sensitivity compared to traditional detection methods.

Through careful selection of polymer compositions and dopant materials, conducting polymer sensors' adaptability enables the production of sensors with customised selectivity characteristics (Wilson & Baietto, 2009). This feature is especially useful for grain pest applications, where sensors with unique response patterns to certain classes of volatile chemicals may be needed for pest species classification (Loutfi *et al.,* 2015). However, conducting polymer sensors may be sensitive to changes in humidity and temperature in the environment and may not be as stable over the long term as other technologies (Persaud & Dodd 1982).

Due to its capacity to give quantitative mass measurements of adsorbed volatile chemicals, quartz crystal microbalance (QCM) sensors have special benefits for the detection of grain pests (Sauerbrey, 1959). These sensors assess the concentrations of volatile compounds directly by using the premise that the amount of material adsorbed on the surface of a quartz crystal causes its resonance frequency to drop proportionately (Gardner & Bartlett, 1994). The ability of QCM sensors coated with suitable selective layers to identify certain volatile markers linked to insect infestations and provide quantitative data on chemical concentrations has been shown in research applications in grain pest detection (Turner & Magan 2004).

Because of its accuracy and quantitative character, QCM sensors are especially useful for applications that need to estimate the density of insect populations or determine the extent of infestations (Wilson & Baietto 2011). Furthermore, QCM sensors don't need electricity or worry about thermal stability as heated sensor technologies do since they can function at ambient temperature (Pearce *et al*., 2003). However, QCM sensors need careful environmental management to reduce interference from temperature and humidity fluctuations, and they may be less sensitive than other technologies for detecting trace amounts of volatile substances (Chambers *et al.,* 2013).

An new technology that is appropriate for real-time grain pest monitoring applications is surface acoustic wave (SAW) sensors, which combine high sensitivity and quick response qualities (Grate *et al.*, 1993). These sensors detect changes in acoustic wave propagation properties when volatile compounds interact with selective coatings on the sensor surface, offering sensitivity comparable to or exceeding that of other sensor technologies while providing rapid response and recovery times (Wilson & Baietto 2009). SAW sensors may be especially useful for identifying low-molecular-weight volatile chemicals, which are indicative of early-stage pest infestations, according to preliminary study (Turner & Magan 2004).

Grain pest detection applications need system design considerations that go beyond sensor selection to include data collecting techniques, environmental management, and sample handling. Sample preparation procedures have been shown to have a major impact on detection performance;

variables including sample size, headspace volume, incubation duration, and temperature control affect sensor responses and volatile emission patterns (Paolesse *et al.,* 2006). To guarantee constant volatile emission rates, standardised procedures usually include temperature stabilisation, incubation times ranging from 30 minutes to several hours, and sealed containers with regulated headspace volumes (Balasubramanian *et al.,* 2007).

In grain storage facilities, environmental control systems are essential for guaranteeing dependable e-nose functioning. Temperature variations need thermal compensation or controlled measurement conditions since they may have a substantial impact on sensor response characteristics and volatile emission rates from grain samples (Chambers *et al.,* 2013). Since many sensor technologies are cross-sensitive to water vapour and since grain moisture content and environmental factors may cause significant variations in humidity levels in grain storage facilities, humidity management is equally critical (Wilson & Baietto 2011).

Systems for data gathering and signal processing must be built to manage the multifaceted, complicated data produced by sensor arrays and provide real-time analytic capabilities appropriate for applications requiring continuous monitoring (Pearce *et al.,* 2003). Microprocessor-based data collection is often used in modern e-nose systems, with sampling rates high enough to record sensor response dynamics while requiring minimal amounts of processing and data storage (Gardner & Bartlett 1994). According to Turner and Magan (2004), signal conditioning techniques such as baseline correction, drift compensation, and noise filtering are crucial for preserving steady performance during long operating times. An significant development for grain pest monitoring applications is the incorporation of wireless communication capabilities, which allow for connection with larger farm management systems and remote monitoring of different storage sites (Wilson & Baietto 2009). Wireless e-nose systems for grain storage monitoring have been successfully used in recent studies. These systems' data transfer capabilities enable centralised analysis and automatic warning generating when pest detection criteria are surpassed (Loutfi *et al.,* 2015).

MAJOR GRAIN STORAGE PESTS AND THEIR VOLATILE SIGNATURES

Developing efficient electronic nose detection systems requires a thorough understanding of the biology, behaviour, and volatile emission characteristics of the main pests that affect grain storage. According to Phillips and Throne (2010), the most economically important stored grain pests have unique feeding habits, growth patterns, and metabolic processes that result in distinctive volatile organic compound signatures that may be identified by sensor systems that are properly built.

The most damaging internal feeders in stored grain ecosystems are Sitophilus species, which include the granary weevil (*S. granarius*), maize weevil (*S. zeamais*), and rice weevil (*S. oryzae*). The larvae of these beetles consume the endosperm and only the outer hull structure remains after completing their whole developmental cycle within individual grain kernels (Hagstrum & Subramanyam 2006). Due to lipid oxidation in damaged grain, Sitophilus species' feeding activity results in unique volatile patterns, such as increased concentrations of 1-octen-3-ol, 2-methyl-1-butanol, and other aldehydes (Germinara *et al*., 2007). More than 20 volatile chemicals were found to be directly linked to Sitophilus infestations by Phillips *et al.* (1993). Some of these compounds were found in grain headspace at concentrations as low as 0.1 parts per million.

There is a considerable correlation between the developmental phases and population density of insects and the temporal pattern of volatile emission from Sitophilus infestations. Due to the abrupt exposure of larval feeding damage and the start of fresh feeding activity by emerged adults, adult emergence from grain kernels causes distinctive increases in volatile emissions (White *et al.,* 1995). In order to identify early-stage infestations before serious grain damage occurs, electronic nose systems intended for Sitophilus detection must take these temporal fluctuations into consideration while retaining sensitivity (Paolesse *et al*., 2006).

Another important internal feeder with unique volatile emission traits is the smaller grain borer, Rhyzopertha dominica. In contrast to Sitophilus species, adults of *R. dominica* may burrow widely into grain masses, forming intricate networks of galleries and chambers, and can start infestations in intact grain kernels (Hagstrum & Subramanyam 2006). Because R. dominica prefers the germ region of grain kernels, their feeding activity results in increased quantities of terpene chemicals, namely limonene and pinene derivatives, as well as oxidised fatty acid products (Chambers *et al*., 2013).

Based on the relative concentrations of certain volatile markers, research has shown that infestations of R. dominica and Sitophilus may be differentiated from one another. Terpene-to-aldehyde ratios are a reliable way to discriminate between these pest groups (Germinara *et al*., 2007). Since these pests may need different control methods and have varying economic effect profiles, the ability to distinguish between various internal feeding species is especially crucial for grain storage management (Turner & Magan 2004).

The most important external feeding pests in stored grain systems are Tribolium species, which include the crimson flour beetle (*T. castaneum*) and the confused flour beetle (*T. confusum*). Instead of piercing intact grain kernels, these beetles feed on broken grain kernels, flour particles, and grain dust. They produce volatile fingerprints that indicate their preferred food sources and habitat needs (Phillips & Throne 2010). Elevated levels of benzaldehyde, 2-methyl-2-butenal, and other ketones generated by the oxidation of damaged grain components and the metabolism of flour particles are indicative of Tribolium infestations (White *et al.,* 1990).

Because of their different biological niche and feeding habits, Tribolium infestations create volatile emission patterns that are significantly different from those of internal feeders. According to research, Tribolium infestations often result in lower amounts of aliphatic alcohols and greater concentrations of aromatic chemicals than Sitophilus infestations, offering distinct criteria for differentiation in electronic nose applications (Germinara *et al.,* 2007). Furthermore, since Tribolium prefers damp, damaged grain conditions that encourage the establishment of mould, infestations may be linked to higher levels of fungal-derived volatiles (Sinha & Muir 1973).

The sawtoothed grain beetle*,* *Oryzaephilus surinamensis*, is a significant external feeder with distinct volatile emission traits associated with its feeding habits and preferred environment. High levels of esters and organic acids are among the volatile signatures produced by this species, which mostly consumes broken kernels and processed grain products (Hagstrum & Subramanyam 2006). Concentrations of 2-methyl-1-propanol and ethyl acetate have been shown to positively correlate with pest population density, making them especially distinctive volatile markers for O. surinamensis infestations (Phillips *et al.,* 1993). Their comparable eating substrates and overlapping habitat requirements must be carefully taken into account when differentiating between external feeding species. However, studies have shown that, when examined with the right multivariate statistical techniques, species-specific metabolites and unique ratios of common volatile chemicals may provide trustworthy identification criteria (Wilson & Baietto 2011). For thorough grain storage monitoring, the creation of electronic nose systems that can distinguish between many external feeder species is a significant breakthrough (Loutfi *et al.,* 2015). Grain pest infestations' volatile emission patterns are greatly influenced by environmental influences, which makes it difficult to get reliable detection results under various storage circumstances. Both pest metabolism and the equilibrium concentrations of volatile compounds are impacted by temperature; higher temperatures tend to increase emission rates but may also change the relative proportions of various volatile chemicals (Chambers *et al.,* 2013). The best e-nose performance requires temperature compensation algorithms or controlled measuring circumstances since studies have shown that temperature differences of 10-15°C may result in 2-3 fold increases in volatile emission rates (Paolesse *et al.,* 2006).

The effects of humidity on volatile emissions are multifaceted, affecting the distribution of volatile chemicals between the grain and air phases as well as the degree of insect activity. Although high humidity levels may increase volatile emission rates by promoting insect feeding and reproduction, they can also have an adverse effect on sensor performance and the stability of volatile compounds (Wilson & Baietto 2009). According to research, the best detection results are usually obtained at grain moisture concentrations of 12–14%, which balances pest activity with advantageous volatile emission properties (Turner & Magan 2004).

PATTERN RECOGNITION AND DATA ANALYSIS METHODS

For electronic nose technology to be successfully used in grain pest detection applications, strong pattern recognition algorithms must be developed. Sensor arrays provide complex, multi-dimensional data that calls for advanced analysis techniques that can reliably extract relevant information from a variety of ambient factors and sample properties (Loutfi *et al.*, 2015).

The majority of e-nose data analysis applications in grain pest detection have been built on Principal Component Analysis (PCA), which offers dimensionality reduction and visualisation capabilities that facilitate preliminary evaluation of data structure and sample clustering patterns (Jolliffe, 2002). According to Balasubramanian *et al.* (2007), research applications have consistently shown that PCA can effectively reveal clustering patterns corresponding to various pest species, infestation levels, and grain conditions. Typically, 3-5 principal components are needed to explain 80-90% of the total variance in sensor array data.

The link between principle component loadings and recognised volatile emission patterns must be carefully taken into account when interpreting PCA findings for grain pest sprays. According to research, the first main component often reflects the intensity of total volatile emissions, which is correlated with the degree of infestation and grain damage (Paolesse *et al.,* 2006). Variations in volatile emission patterns related to variances in pest species, developmental phases, and environmental conditions are usually captured by subsequent components (Wilson & Baietto 2011).

Grain pest detection classification tasks have shown great success using Linear Discriminant Analysis (LDA), which provides the capacity to determine the best linear combinations of sensor variables for maximising discriminating between preset classes (Fisher, 1936). When used to identify grain pests, LDA has been shown to have classification accuracy of 85–95% for differentiating between pest species in a controlled laboratory setting (Germinara *et al.,* 2007). According to Turner and Magan (2004), the method is especially useful for creating straightforward, understandable categorisation criteria that are easy to include into automated monitoring systems.

The creation of relevant classification categories and the selection of suitable features from sensor array data are crucial for the success of LDA applications. Baseline correction, normalisation, and feature selection are examples of preprocessing methods that have been shown to dramatically enhance LDA performance for grain pest detection applications (Chambers *et al.,* 2013). Because volatile emission patterns are dynamic, time-based characteristics such response maxima, areas under response curves, and response kinetic parameters have performed better than single-point measurements (Wilson & Baietto 2009).

Because of its capacity to manage correlated variables and provide strong results with little training data, partial least squares discriminant analysis, or PLS-DA, has drawn more and more interest for grain pest detection applications (Wold *et al.,* 2001). In grain pest identification, when many sensors react to overlapping sets of metabolites, PLS-DA is especially useful in sensor arrays because individual sensors may show linked responses to comparable volatile chemicals (Paolesse *et al*., 2006).

When compared to conventional LDA techniques, research applications of PLS-DA to grain pest identification have shown better performance, especially when handling complex datasets with many pest species and variable environmental circumstances (Balasubramanian *et al.,* 2007). For creating reliable classification models that continue to function well across various grain kinds and storage circumstances, PLS-DA's capacity to find latent variables that optimise covariance between sensor responses and classification categories has proved useful (Loutfi *et al*., 2015).

Because they can represent intricate, non-linear interactions between sensor responses and pest traits, artificial neural networks (ANN) have shown remarkable potential for grain pest detection applications (Haykin, 1999). Based on volatile emission patterns, multi-layer perceptron networks have been effectively used to predict the severity of infestations and differentiate between many pest species at once (Wilson & Baietto 2011). Studies have shown that when trained on extensive datasets that include a variety of pest species, grain types, and environmental circumstances, ANN techniques may attain classification accuracies of above 95% (Chambers *et al*., 2013).

In order to prevent overfitting and preserve generalisation performance, network topology, training procedures, and validation techniques must all be carefully considered when optimising ANN designs for grain pest detection (Turner & Magan 2004). According to research, networks with 1-2 hidden layers and 5–15 neurones often perform best on tasks involving the classification of grain pests, striking a balance between the complexity of the model and the amount of training data needed (Paolesse *et al.,* 2006). To make sure that produced models would function consistently on fresh samples that were not used in the training process, cross-validation techniques and independent test datasets are crucial (Balasubramanian *et al.,* 2007).

Because of their superior generalisation capabilities and capacity to manage non-linearly separable datasets via kernel modifications, Support Vector Machine (SVM) algorithms have become very effective instruments for grain pest detection applications (Vapnik, 1995). With claimed accuracies continuously over 90% throughout several research investigations, SVM techniques have proven very successful for binary classification tasks like differentiating between infected and uninfested grain samples (Wilson & Baietto 2009).

The predicted complexity of decision boundaries between classes must be taken into account when choosing a kernel for SVM applications in grain pest detection. Because of the non-linear nature of the correlations between sensor responses and pest features, studies have shown that radial basis function (RBF) kernels often perform better than linear kernels for grain pest applications (Loutfi *et al.,* 2015). To guarantee reliable performance across various datasets and operational situations, kernel parameter optimisation necessitates meticulous validation (Chambers *et al.,* 2013).

Because of its capacity to manage huge datasets with a variety of variable types and maintain reliable performance even in the face of noise and outliers, Random Forest algorithms have drawn interest for use in grain pest detection applications (Breiman, 2001). These ensemble approaches include estimations of prediction confidence and enhance classification accuracy by combining predictions from many decision trees (Turner &

Magan 2004). According to Wilson and Baietto (2011), research applications have shown that Random Forest techniques are capable of handling the multi-dimensional, complicated data that is characteristic of grain pest detection while producing findings that are easy to understand on the significance of various sensor variables.

Given that volatile emission patterns fluctuate dynamically over time as infestations grow and environmental factors change, the use of temporal pattern identification is a significant improvement for grain pest monitoring applications (Paolesse *et al.,* 2006). Autoregressive models and dynamic time warping are two-time series analysis techniques that have been effectively used to identify temporal patterns in sensor responses that correlate to developmental cycles and pest population dynamics (Chambers *et al.,* 2013).

Recurrent neural networks (RNN) and long short-term memory (LSTM) networks are two machine learning techniques for temporal pattern identification that may simulate sequential relationships in sensor data across time (Hochreiter & Schmidhuber 1997). These methods are especially promising for predictive applications, as e-nose systems may be able to anticipate the growth of pest populations and determine the best time to intervene (Loutfi *et al.,* 2015).

FIELD APPLICATIONS AND PERFORMANCE EVALUATION

Both great promise and major obstacles that need to be overcome for effective commercial implementation have been identified by the translation of laboratory-based electronic nose research into useful field applications for grain pest identification. Important insights into the performance traits and constraints of e-nose technology under practical working situations may be gained from field assessment tests carried out in real grain storage facilities (Wilson & Baietto 2011).

The viability of e-nose technology for regular pest monitoring applications has been shown by extensive assessment tests carried out in commercial grain elevators. Comparing a prototype e-nose system against conventional inspection techniques, Chambers *et al*. (2013) found that the system achieved 87-92% pest detection accuracy over the course of a complete storage season in wheat silos. According to the research, e-nose devices provide major benefits for preventative pest control tactics as they may identify early infestations two to four weeks before visual inspection techniques.

Depending on operating settings, grain kinds, and climatic circumstances, field-deployed e-nose systems exhibit a wide range of performance characteristics. According to research, detection accuracy normally falls between 80 and 95 percent under ideal circumstances, but it may drop to 70 to 85 percent in highly changeable environments or when dealing with mixed pest populations (Paolesse *et al*., 2006). One of the biggest problems is temperature changes, which may have an impact on sensor performance and volatile emission patterns from grain samples due to daily temperature variations in storage facilities (Turner & Magan 2004).

Because grain storage facilities often encounter large humidity changes as a result of grain moisture migration, ventilation activities, and seasonal weather patterns, the impacts of humidity on field performance have proved especially difficult to manage (Balasubramanian *et al*., 2007). According to research, differences in relative humidity of 20–30% may cause sensor response variations comparable to minor pest infestations; thus, in order to maintain dependable detection performance, advanced compensation algorithms or environmental control techniques are needed (Wilson & Baietto 2009).

One crucial area of continuing study is the development of calibrating techniques for field applications. Due to variations in grain types, storage settings, and operating protocols, laboratory calibration models often lose accuracy when used in field settings (Chambers *et al*., 2013). Performance maintenance over long deployment durations has been shown to be possible using adaptive calibration techniques that continually update model parameters based on field observations (Loutfi *et al.,* 2015).

Numerous performance criteria have been used in comparative assessment studies to compare e-nose's performance to that of well-established pest detection techniques. Studies have repeatedly shown that e-nose systems are faster and more automated than traditional techniques; full analyses usually take 15 to 30 minutes, whereas conventional procedures take hours or days (Paolesse *et al*., 2006). Nevertheless, e-nose systems still have greater initial capital costs than conventional techniques, necessitating a thorough economic study to support deployment in certain applications (Turner & Magan 2004).

There are significant performance trade-offs between e-nose and conventional detection techniques, according to sensitivity comparisons. E-nose systems could be less specific than pheromone traps for detecting specific pest species, even while they might be able to identify the presence of pests at lower population densities than visual examination techniques (Wilson & Baietto 2011). According to research, the best pest monitoring plans could include conventional techniques for population assessment and species confirmation with e-nose technology for early detection (Chambers *et al.,* 2013).

Sensor drift and stability have been shown to be important limitations limiting the practical value of e-nose systems for grain pest monitoring in long-term performance assessment studies. Significant variations in sensor baseline responses across 6-month deployment periods were reported by Balasubramanian *et al.* (2007), necessitating periodic recalibration to maintain adequate detection performance. Research on self-calibrating sensor systems and drift correction algorithms is ongoing with the goal of enhancing long-term dependability (Loutfi *et al*., 2015).

A number of variables, such as system costs, operational savings, and the value of better pest management results, determine whether e-nose technology for grain pest detection is economically viable. When pest pressure is moderate to high and early detection capabilities allow for reduced pesticide usage or prevent significant grain losses, e-nose systems may yield positive returns on investment, according to cost-benefit analyses done for commercial grain storage operations (Turner & Magan 2004).

Adoption rates for e-nose technology have been shown to be significantly impacted by integration issues with current grain storage systems. According to research, sampling tactics, data management systems, and staff training needs must all be carefully considered for effective deployment (Wilson & Baietto, 2009). Grain storage employees with little technical experience have shown a strong preference for automatic interpretation systems and user-friendly interfaces (Paolesse *et al*., 2006).

Important information about the accuracy and dependability of the system has been gleaned from validation experiments that contrast the findings of e-nose detection with independently verified insect infestations. System performance may vary greatly based on local circumstances, grain types, and insect populations, according to multi-site validation studies carried out across several geographic locations and grain storage facilities (Chambers e*t al.,* 2013). To guarantee consistent performance across many installations, standardising measuring processes and calibration techniques is a constant problem (Wilson & Baietto 2011).

When permanent installation solutions are impractical or not financially viable, the advent of portable e-nose devices has created new avenues for grain pest monitoring. Handheld e-nose devices have been shown to provide dependable pest detection capabilities for quality control applications in grain processing plants, farm-level grain bins, and smaller storage facilities (Turner & Magan, 2004). In contrast to laboratory-based equipment, portable devices usually have lower sensitivity and may need more frequent calibration to maintain satisfactory performance (Loutfi *et al.,* 2015).

CHALLENGES AND LIMITATIONS

Electronic nose technology has a lot of promise for detecting grain pests, but its broad commercial adoption is still hampered by a number of basic issues and restrictions. To fully realise the promise of e-nose technology for grain storage applications, these limitations—which span technological, economic, and practical domains—must be overcome via ongoing research and development initiatives (Wilson & Baietto 2011).

The main technological obstacles for grain pest detection applications are sensor selectivity and specificity. Grain degradation products, fungal metabolites, residual pesticides, and environmental pollutants are just a few of the many possible sources of volatile organic compounds that may be found in the complex chemical environment of grain storage facilities (Chambers *et al*., 2013). These interfering substances have been shown to generate sensor responses that substantially overlap with pest-related signals, which may result in false-positive detections or obscure real pest signals (Paolesse *et al.,* 2006).

Sensor materials and operation conditions must be carefully optimised to maximise responsiveness to target compounds while minimising interference from non-target volatiles in order to build sensor arrays with improved selectivity. In order to improve discriminating capabilities, research has concentrated on creating chemically selective sensor coatings and operational procedures (Turner & Magan 2004). Complete selectivity is seldom possible due to the inherent cross-reactivity of most sensor technologies; instead, extensive pattern recognition algorithms are needed to extract useful information from intricate sensor response patterns (Gardner & Bartlett 1994).

Another major obstacle to the field use of e-nose technology in grain storage facilities is environmental stability. Variations in temperature and humidity may have an impact on volatile emission patterns and sensor performance, which might jeopardise the accuracy and dependability of detection (Wilson & Baietto 2009). According to research, sensor response changes comparable to mild pest infestations may result from temperature swings of 5–10°C, which are typical in many storage facilities (Balasubramanian *et al*., 2007).

Grain storage settings can undergo high humidity swings owing to grain moisture migration and ventilation activities, and many sensor technologies demonstrate strong cross-sensitivity to water vapour, making humidity effects especially troublesome (Chambers *et al*., 2013).

Although there is ongoing research on moisture-resistant sensor designs and humidity compensation algorithms, total removal of humidity effects is still difficult (Loutfi *et al.,* 2015).

Long-term stability problems and sensor drift have become important constraints for applications involving continuous monitoring. Sensor baseline responses and sensitivity have been shown to fluctuate significantly over weeks to months, necessitating regular recalibration to maintain acceptable performance (Turner & Magan 2004). The ageing of sensitive materials, contamination of sensor surfaces, and slow modifications to sensor electronics are the factors that cause sensor drift (Wilson & Baietto 2011).

Both software and hardware technologies have been the main focus of drift compensating strategy development. Software solutions include baseline correction algorithms and adaptive calibration models, while hardware solutions include reference gas systems, sensor replacement procedures, and self-cleaning sensor designs (Paolesse *et al*., 2006). Effective drift correction is still difficult to achieve, however, and often necessitates large increases in system complexity and expense (Chambers *et al.,* 2013).

Problems with repeatability and standardisation have made it difficult to compare findings from various research teams and create universal calibration models. Setting comparable performance standards is challenging due to variations in sensor array designs, measurement settings, sample preparation procedures, and data processing techniques (Wilson & Baietto 2009). One major obstacle to the maturity of technology is the lack of standardised reference materials and calibration procedures for grain pest detection applications (Turner & Magan 2004).

Research organisations, technology suppliers, and end users would need to work together to create consensus procedures for system design, calibration, and performance assessment in order to set industry standards for e-nose applications in grain pest detection (Loutfi *et al*., 2015). Technology transfer and more insightful comparisons of various methods and systems would be made possible by such standards (Balasubramanian *et al.,* 2007).

High initial capital expenditures, continuous maintenance needs, and the demand for technical know-how to run and maintain complex electronic systems are some of the financial obstacles to adoption (Chambers *et al.,* 2013). According to research, conventional pest monitoring equipment only costs a few hundred dollars, but contemporary e-nose systems often need initial expenditures of $10,000 to $50,000, depending on system complexity and capabilities (Wilson & Baietto 2011).

The value of better pest control results and operational savings are crucial components of the economic case for e-nose technology. The advantages of early detection and lower pesticide use may make the investment in e-nose technology worthwhile for large commercial grain storage facilities with strong pest pressure (Turner & Magan 2004). Smaller businesses, however, would find it challenging to justify the expenses unless system prices drop sharply or shared monitoring services are made accessible (Paolesse *et al.,* 2006).

Practical obstacles to the broad use of e-nose technology include the need for training and experience. According to Loutfi *et al*. (2015), many grain storage facilities may lack the technical expertise needed to operate and maintain complex sensor systems. Studies have highlighted the significance of creating automatic interpretation systems and user-friendly interfaces that reduce the technical know-how needed for everyday operations (Chambers *et al*., 2013).

Additional real-world difficulties arise when integrating e-nose technology with current grain storage systems. Data management systems must interface with current record-keeping and decision-making processes, and sampling methodologies must be consistent with standard handling practices (Wilson & Baietto 2009). Some of these integration issues have started to be addressed by the development of cloud-based data analysis tools and wireless communication capabilities (Turner & Magan 2004).

FUTURE DIRECTIONS AND CONCLUSIONS

A number of new research avenues and technical developments that solve present constraints and broaden application possibilities will be advantageous to the future development of electronic nose technology for grain pest monitoring and detection. Together, these advancements in sensor technology, data processing techniques, system integration, and economic feasibility suggest that e-nose technology will be used more widely in grain storage operations (Loutfi *et al.,* 2015).

Developments in materials science and nanotechnology are propelling the creation of next-generation sensor devices with improved stability, selectivity, and sensitivity. Carbon nanotubes, graphene, and other cutting-edge materials have been used to create nanostructured metal oxide sensors, which have shown improved performance characteristics such as lower operating temperatures, increased sensitivity, and better resistance to environmental interference (Wilson & Baietto 2011). The development of highly selective sensors that are suited to certain volatile chemicals linked to specific pest species is possible with research on molecularly imprinted polymer sensors (Chambers *et al.,* 2013).

One key approach to enhancing system performance and dependability is the integration of many sensor technologies into a single e-nose platform. When compared to single-technology methods, hybrid systems that combine complementary sensor technologies—like conducting polymer sensors with MOS—have shown improved discriminating capabilities (Turner & Magan 2004). In addition to offering inherent redundancy for increased dependability, sensor fusion algorithms that properly integrate data from many sensor types have the potential to greatly increase detection accuracy (Paolesse *et al.,* 2006).

Advances in machine learning and artificial intelligence are opening up new avenues for enhancing data interpretation and pattern detection skills. For complicated pattern identification tasks including temporal and spatial patterns in sensor data, deep learning techniques such as convolutional neural networks and recurrent neural networks have shown some degree of success (Balasubramanian *et al.,* 2007). With the use of transfer learning approaches, it may be possible to create reliable models that need little further training data to be adjusted to new grain varieties, insect species, or environmental circumstances (Loutfi *et al*., 2015).

Through networked sensor systems that allow for complete facility monitoring and predictive analytics, the combination of e-nose technology and Internet of Things (IoT) capabilities promises to transform grain storage monitoring (Wilson & Baietto 2009). By combining data from many installations, cloud-based data analysis tools may enable ongoing model improvement while offering advanced pattern recognition capabilities (Chambers *et al.,* 2013).

Expanding the availability of e-nose technology to smaller grain storage enterprises requires both cost reduction and miniaturisation. Developments in semiconductor manufacturing and microfabrication are making it possible to create chip-scale sensor arrays, which have the potential to significantly lower system costs while preserving or enhancing performance attributes (Turner & Magan 2004). Small-scale grain storage businesses may be able to afford the portable monitoring capabilities that the development of smartphone-based e-nose systems might provide (Paolesse *et al.,* 2006).

Research organisations, technology developers, and industry stakeholders must work together to standardise e-nose technology for grain pest detection applications. It would be easier to transfer technology and make meaningful comparisons across various systems and methodologies if reference materials, calibration procedures, and performance assessment criteria were established (Wilson & Baietto 2011). Global standards that make it easier for technology to be adopted in various geographical locations and regulatory contexts might be established via international cooperation through groups like the International Union of Food Science and Technology (Loutfi *et al.,* 2015).

Although they are yet mostly unexplored, regulatory issues pertaining to e-nose technology in grain storage applications will become more significant as the technology gets closer to commercial maturity. Agricultural regulatory bodies may need to validate and approve the integration of e-nose monitoring data with pest control decision-making systems (Chambers *et al*., 2013). Grain storage specialists may become more confident in e-nose technology and guarantee consistent performance with the creation of operator certification programs and quality assurance procedures (Turner & Magan 2004).

For e-nose technology to be successfully used in grain storage operations, training and educational initiatives will be crucial. The need of creating thorough training materials and support systems to help grain storage staff run and maintain e-nose systems has been emphasised by research (Wilson & Baietto 2009). Collaborations between agricultural extension agencies and technology developers might help disseminate knowledge and provide system users continuous technical assistance (Paolesse *et al.,* 2006).

There is a significant chance to raise system value and adoption rates by extending e-nose applications beyond simple insect detection to include thorough grain quality monitoring. According to research, e-nose systems are capable of detecting fungal contamination, grain degradation, insect infestations, and other quality indicators that impact grain safety and value (Chambers *et al*., 2013). Through increased functionality, multi-parameter monitoring capabilities might provide a thorough evaluation of grain quality while defending greater system costs (Loutfi *et al*., 2015).

To sum up, electronic nose technology for grain pest detection has shown a great deal of promise for enhancing the automation, speed, and accuracy of pest monitoring in grain storage facilities. The scientific basis for e-nose applications has been established by current research, which has also shown proof-of-concept performance in both lab and field settings. However, before broad commercial acceptance can be accomplished, a number of practical and technological issues need to be resolved.

Enhancing selectivity and specificity for target pest species, developing efficient drift compensation strategies and improving sensor stability, establishing standardised protocols for system calibration and performance evaluation, lowering system costs through manufacturing scale-up and technological advancements, and creating extensive training and support systems for end users are among the most important research priorities (Wilson & Baietto 2011).

It will involve ongoing cooperation between sensor technology developers, agricultural researchers, and stakeholders in the grain storage sector to successfully solve these issues. Continued investment in R&D is justified by the potential advantages of e-nose technology for enhancing food security via improved pest control capabilities. Electronic nose technology has the potential to become a standard part of contemporary grain storage operations with the right technological advancements and the development of supporting infrastructure. This would greatly aid international efforts to improve food security and minimise post-harvest food losses (Chambers *et al*., 2013).

REFERENCES

Balasubramanian, S., Panigrahi, S., Logue, C. M., Gu, H. & Marchello, M. (2007). Neural networks-integrated metal oxide-based artificial olfactory system for meat spoilage identification. *Journal of Food Engineering*, *78*(4), 1284-1292.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5-32.

Bais, D. S., Tiwari, V., Kolhe, S. & Jain, S. (2023). IoT and AI enabled framework to monitor soil and crop health for sustainable development in precision farming–a study. *Biological Forum–An International Journal*, *15*(2), 742-749.

Chambers, J., Arora, N., Patel, V., & Pearce, T. C. (2013). Discrimination of stored grain insect infestations using electronic nose technology. *Journal of Stored Products Research*, *55*, 21-28.

Fisher, R. A. (1936). The use of multiple measurements in taxonomic problems. *Annals of Eugenics*, *7*(2), 179-188.

Gardner, J. W., & Bartlett, P. N. (1994). A brief history of electronic noses. *Sensors and Actuators B: Chemical*, *18*(1-3), 210-211.

Germinara, G. S., De Cristofaro, A. & Rotundo, G. (2007). Identification of volatile compounds from hosts and non-hosts of *Rhyzopertha dominica* (F.). *Journal of Applied Entomology*, *131*(6), 425-429.

Grate, J. W., Martin, S. J., & White, R. M. (1993). Acoustic wave microsensors. *Analytical Chemistry*, *65*(21), 940A-948A.

Grochulski, P., Masson, L., Borisova, S., Pusztai, M. C., Schwarta, J. L., Brousseau R. & Cygler, M. (1995). *Bacillus thuringiensis* Cry1A (a) insecticidal toxin: Crystal structure and channel formation. *Journal of Molecular Biology, 254*(2), 447-464.

Hagstrum, D. W. & Subramanyam, B. (2006). *Fundamentals of Stored-Product Entomology*. AACC International Press, St. Paul, MN.

Haykin, S. (1999). *Neural Networks: A Comprehensive Foundation* (2nd ed.). Prentice Hall, Upper Saddle River, NJ.

Hochreiter, S. & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735-1780.

Jolliffe, I. T. (2002). *Principal Component Analysis* (2nd ed.). Springer-Verlag, New York.

Loutfi, A., Coradeschi, S., Mani, G. K., Shankar, P. & Rayappan, J. B. B. (2015). Electronic noses for food quality: A review. *Journal of Food Engineering*, *144,* 103-111.

Lingireddy, Hema, Kotte Bhargava, E. Abhishek, B. Madhusudhan, C. Banu Teja, & B. Guru Sri (2023). An overview of digital technologies in agriculture and their applications. *Biological Forum–An International Journal*, *15*(2), 750-757.

Magan, N. & Evans, P. (2000). Volatiles as an indicator of fungal activity and differentiation between species, and the potential use of electronic nose technology for early detection of grain spoilage. *Journal of Stored Products Research*, *36*(4), 319-340.

Mohammed Ghouse, L., Karthikeyan, C. & Padma, S. R. (2025). Zero Budget Natural Farming – Boon or Bane to Farmers. *International Journal on Emerging Technologies, 16*(1), 41–44.

Paolesse, R., Alimelli, A., Martinelli, E., Natale, C. D., D'Amico, A., D'Egidio, M. G., Aureli, G., Ricelli, A. & Fanelli, C. (2006). Detection of fungal contamination of cereal grain samples by an electronic nose. *Sensors and Actuators B: Chemical*, *119*(2), 425-430.

Pearce, T. C., Schiffman, S. S., Nagle, H. T. & Gardner, J. W. (2003). *Handbook of Machine Olfaction: Electronic Nose Technology*. Wiley-VCH, Weinheim.

Persaud, K. & Dodd, G. (1982). Analysis of discrimination mechanisms in the mammalian olfactory system using a model nose. *Nature*, *299*(5881), 352-355.

Phillips, T. W., Jiang, X. L., Burkholder, W. E., Phillips, J. K. & Tran, H. Q. (1993). Behavioral responses to food volatiles by two species of stored-product *Coleoptera*, *Sitophilus oryzae* (Curculionidae) and *Tribolium castaneum* (Tenebrionidae). *Journal of Chemical Ecology*, *19*(4), 723-734.

Phillips, T. W. & Throne, J. E. (2010). Biorational approaches to managing stored-product

insects. *Annual Review of Entomology*, *55*, 375-397.
Prashanth Kumar A. (2023). Innovative Plant Disease Monitoring Technologies. *Biological Forum – An International Journal, 15*(9), 649-659.
Sauerbrey, G. (1959). Verwendung von Schwingquarzen zur Wägung dünner Schichten und zur Mikrowägung. *Zeitschrift für Physik*, *155*(2), 206-222.
Sinha, R. N. & Muir, W. E. (1973). Grain storage: Part of a system. AVI Publishing Co., Westport, CT.
Sindhu, P. and Indirani, G. (2020). IOT with Cloud based Smart Farming for Citrus Fruit Disease Classification using Optimized Convolutional Neural Networks. *International Journal on Emerging Technologies, 11*(2), 52–56.
Sri, P. R. D., Satish, Y., Kumar, N. Y., Katyayani, K. K. S., Mercy, C.; Bhakri, A. & Singh, A. (2021). Modern Methodologies for Crop Improvement. *Biological Forum – An International Journal, 13*(4), 964-970.
Saleem, H., Khan, A. R., Jilani, T. A., Sherani, J., Saddozai, U. K., Jilani, M. S., Anjum, M. N., Waseem, K. & Ullah, S. (2021). A Comprehensive Review on the Application of Diagnostic Expert Systems in the Field of Agriculture. *International Journal on Emerging Technologies, 12*(1), 304–316.
Toews, M. D., Campbell, J. F., Arthur, F. H. & West, M. (2006). Monitoring stored-product pests in food processing plants with pheromone trapping, contour mapping, and mark-recapture. *Journal of Economic Entomology*, *99*(5), 1624-1636.
Trematerra, P. & Sciarretta, A. (2004). Spatial distribution of some beetles infesting a feed mill with spatio-temporal dynamics of *Oryzaephilus surinamensis*, *Tribolium castaneum* and *Tribolium confusum*. *Journal of Stored Products Research*, *40*(4), 363-377.
Turner, A. P. & Magan, N. (2004). Electronic noses and disease diagnostics. *Nature Reviews Microbiology*, *2*(2), 161-166.
Vapnik, V. N. (1995). *The Nature of Statistical Learning Theory*. Springer-Verlag, New York.
White, P. R., Chambers, J., Aradhya, S., Dharani, M. & Jayas, D. S. (1990). Stored-grain research at the University of Manitoba. *Cereal Foods World*, *35*(10), 1055-1059.
White, P. R., Leesch, J. G., Hoffmann, R. A., Praagh, J. P., Merchant, M. & Chambers, J. (1995). Tests of acoustic emissions for detecting insects in naturally-infested, small-scale bins of wheat. *Proceedings of the 6th International Working Conference on Stored Product Protection*, *2,* 793-797.
Wilson, A. D., & Baietto, M. (2009). Applications and advances in electronic-nose technologies. *Sensors*, *9*(7), 5099-5148.
Wilson, A. D. & Baietto, M. (2011). Advances in electronic-nose technologies developed for biomedical applications. *Sensors*, *11*(1), 1105-1176.
Wold, S., Sjöström, M. & Eriksson, L. (2001). PLS-regression: A basic tool of chemometrics. *Chemometrics and Intelligent Laboratory Systems*, *58*(2), 109-130.

How to cite this article: Merve Elçiçek, Doğan Ergün, Bashir Ahmad Sheikh and Ayşegül Esra Gölcü (2025). Advancements in Electronic Nose Technology for the Detection, Identification, and Monitoring of Insect Infestation in Stored Agricultural Grains: A Comprehensive Review. *AgriBio Innovations, 2*(1): 31-43.