Smart Agricultural Technology 13 (2026) 101849

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

Smart sensing of *Leptinotarsa decemlineata* infestations using a portable optical array

Sheila Sánchez-Artero [a,b], Inmaculada García-Robles [c], M. José López-Galiano [c], Carolina Rausell [c], Pablo Gaviña [a], Pedro Amorós [d], Jose Vicente Ros-Lis [a,b,*]

[a] Instituto Interuniversitario de Reconocimiento Molecular y Desarrollo Tecnológico (IDM), Universitat Politècnica de València, Universitat de València, Doctor Moliner 50, Burjassot, Valencia 46100, Spain

[b] REDOLí research group, Universitat de València, Doctor Moliner 50, Burjassot, Valencia 46100, Spain

[c] Departamento de Genética, Facultad de Ciencias Biológicas, Universitat de València, Avda. Vient Andrés Estelles, 19, Burjassot, Valencia, 46100, Spain

[d] Institut de Ciència dels Materials (ICMUV), c/Catedrático José Beltrán 2, Paterna, 46980 Valencia, Spain

A R T I C L E I N F O

Keywords:
E-nose
Pest
Insect
Leptinotarsa decemlineata
Optical array
ANN
PLS-DA

A B S T R A C T

Leptinotarsa decemlineata is considered one of the most destructive coleopteran pests worldwide, due to its remarkable ability to adapt to diverse environmental conditions. This study presents the design and validation of an innovative, low-cost tool based on an optical array of 12 chemical sensors supported on materials for the specific detection of *L. decemlineata* infestation on *Solanum tuberosum*. Principal component analysis (PCA) evidenced the potential discriminative capacity of the system, showing a clear separation between infested and non-infested samples. Furthermore, models developed by Partial Least Squares Discriminant Analysis (PLS-DA) achieved optimal classification performance (accuracy, precision and sensitivity = 1.000), confirming the high efficiency of the system under controlled experimental conditions. Further validation using artificial neural network (ANN) models reinforced these findings, also obtaining satisfactory performance parameters and no evidence of overfitting, although data would benefit from a larger dataset. Overall, the results obtained support the potential of the optical array as a tool to support early detection of *L. decemlineata*, facilitating its implementation in integrated pest management (IPM) strategies in potato crops, and contributing to more accurate and sustainable decision-making in agriculture.

1. Introduction

The Colorado potato beetle (*Leptinotarsa decemlineata*), one of the most destructive coleopteran pests worlwide, significantly reduces *Solanum tuberosum* production [1,2]. Its success as an invasive organism is attributed to its high fertility, polyphagous behaviour, and strong adaptive capacity to changing environmental conditions, allowing it to establish in new areas [3]. The rapid emergence of resistance to several classes of insecticides, including pyrethroids, carbamates, neonicotinoids, and organophosphates, has severely compromised the effectiveness of chemical control techniques. This highlights the importance of more sustainable integrated management strategies [4–6].

Detection of *L. decemlineata* has been approached through multidisciplinary strategies that integrates visual, molecular, genetic and biological tools, combining traditional methods with emerging technologies to improve accuracy in the identification and monitoring of this pest [7]. The most common and straightforward method remains visual inspection, which identifies adults, larvae, eggs and characteristic symptoms of infestation, such as partial or total defoliation of foliage. Although accessible, it is time consuming technique, its effectiveness depends on the experience of the technician and has significant limitations in early stages of pest development. In parallel, the use of molecular tools has enabled substantial progress in specific detection and population monitoring. However, these approaches often require destructive sampling procedures, highly specialised personnel, laboratory equipment and analysis times that hinder their routine application on a large scale and in field conditions. Remote sensing has emerged as an innovative and promising tool for the indirect identification of damage caused by agricultural pests. The experimental use of drones

* Corresponding author at: Instituto Interuniversitario de Reconocimiento Molecular y Desarrollo Tecnológico (IDM), Universitat Politècnica de València, Universitat de València, Doctor Moliner 50, Burjassot, Valencia 46100, Spain.

E-mail address: J.Vicente.Ros@uv.es (J.V. Ros-Lis).

https://doi.org/10.1016/j.atech.2026.101849
Received 24 November 2025; Received in revised form 31 January 2026; Accepted 1 February 2026
Available online 2 February 2026

equipped with multispectral and thermal cameras has shown remarkable efficiency in detecting plant stress induced by insect-induced defoliation [8]. Complementarily, hyperspectral based detection systems allow early identification of physiological disturbances in plants before visible symptoms become apparent, thus facilitating early and non-invasive detection of infestations [9], including their application in potato fields affected by *L. decemlineata* [10]. Despite their advantages, these technologies have significant limitations, such as high acquisition and operating costs, dependence on environmental and light conditions, complexity of data processing and interpretation, and their predominantly indirect nature, as they detect plant stress rather than the specific presence of the insect. Taken together, these shortcomings highlight the need to develop complementary methods that allow for early, specific, non-invasive, and operationally viable detection of *L. decemlineata* under real field conditions. In this context, the analysis of volatile organic compounds (VOCs) is proposed as a complementary approach based on monitoring the biochemical responses directly induced by plant–pest interaction. This approach allows for the exploration of early signals associated with the presence of the insect, generated before visible damage or physiological alterations become apparent at the macroscopic level.

In recent years, there has been a marked increase in scientific interest in understanding the role of volatile organic compounds (VOCs) in various plant physiological processes, including growth, development and defence mechanisms [11,12]. Within this framework, it has been shown that plants can generate specific biochemical responses depending on the type of pest attacking them, showing distinct patterns against insects with different feeding habits, such as *L. decemlineata* (potato beetle) and *Myzus persicae* (green peach aphid) [1]. Furthermore, VOC emissions by potato plants play a crucial role in attracting or repelling insect pests [2]. Recent studies indicate that the VOCs emitted by these plants are not only involved in pest defence but also play essential roles in plant development and in the regulation of interactions with beneficial microorganisms [13,14].

Among the emerging tools for detection based on volatile organic compounds, electronic noses stand out. These systems use pattern recognition algorithms to identify volatile profiles characteristic of a given matrix. These technologies have been widely and successfully applied in the food industry, where they have been used with great effectiveness for the detection of contaminants and the evaluation of product freshness [15,16]. Their application in agriculture includes the development of electronic noses equipped with gas sensors and near-infrared spectroscopy for the early detection of aphids in wheat crops[17], as well as their use in the identification of microbial pests in plants [18,19] and in the detection of VOCs released by plants in response to attack by invasive species [20]. These applications position electronic noses as innovative, non-invasive alternatives for the early pest diagnosis. Furthermore, their integration into precision agriculture has enabled the development of systems for soil-condition monitoring [21].

Among the different types of electronic noses, optoelectronic noses represent an evolution of systems based exclusively on electrochemical sensors. Although the latter have been widely explored and show a low cost, they can have limitations in terms of selectivity and stability in presence of complex chemical interference, especially when analysing biological matrices rich in volatile compounds. Also, dyes are generally cheap, have the potential to offer a varied chemical reactivity, and the possibility to use optical detection systems to extract the sensor response. In this context, optoelectronic noses, integrating electrochemical with optical sensors, have the potential to provide a high cost-effectiveness, portability and response specificity for the characterisation of complex chemical profiles using pattern recognition algorithms.

This hybrid approach has been successfully applied to the detection of VOC profiles emitted during the composting process, combining optical and electrochemical gas sensors with pattern recognition algorithms [22,23]. Although individual optical sensors had been described previously, these approaches constituted the first implementations of multi-source detection tools capable of integrating signals of different natures to increase the specificity of the overall response. Similarly, studies have been published that use colorimetric sensor arrays to identify volatiles associated with the freshness of meat products, such as chicken [24,25], highlighting the potential of optoelectronic systems for the rapid and specific recognition of complex chemical signatures.

Despite the advances described above, there remains a significant gap in the early and specific detection of *L. decemlineata*. Most existing studies are based on indirect methods that identify damage or plant stress once the infestation is advanced, or on analytical techniques aimed at identifying individual volatile compounds, which require complex instrumentation and are not easily transferable to the field. Furthermore, although electronic nose systems have been explored in agricultural contexts, their specific application to the early detection of *L. decemlineata* using hybrid optoelectronic devices capable of integrating optical and electrochemical signals for the recognition of global VOC patterns has not been systematically addressed. This lack of non-invasive, specific and operationally viable tools currently limits the implementation of integrated management strategies based on early detection of the insect.

Thus, we hypothesize that optoelectronic noses-based detection systems, combined with advanced data-analysis techniques can be applied for the early detection of *L. decemlineata*. The proposal envisages a system based on optical sensors as an on-filed, technologically efficient, and cost-effective alternative to more complex analytical methodologies. It should be noted that, although specific volatile compounds associated with the potato's response to insect attack have been identified, this study does not focus on the individual identification of specific chemical species, but rather on the overall analysis of emission profiles and the recognition of characteristic patterns of chemical signatures induced by plant–pest interaction.

2. Materials and methods

2.1. Sensing technology and experimental setup

In this study, a set of optical sensors was used to detect the pest *L. decemlineata*. To define the optical set, an initial screening by exposition of a larger library of sensing units was exposed to a controlled *in vitro* environment with *L. decemlineata*. Afterwards, the optical sensors with the most sensitive and specific colour changes were selected, suitable for characterising the infestation and enabling subsequent comparative studies.

The optical sensors were developed by impregnating inorganic supports with the selected dyes. To do this, the support materials were sonicated for 2 min in the dye solution and then left to stand for 24 h to maximise dye impregnation. Finally, the solvent was evaporated to fix the dye to the solid support. As a result, twelve different optical detection materials were obtained and arranged on ELISA-type plates. To ensure uniformity and reproducibility of the measurements, three replicates of each sensor were used. The twelve sensors used and the ratio of mg of dye per gram of support are summarised in Table 1.

To evaluate the detection system, a series of controlled tests were designed under laboratory conditions to expose the optical sensors to volatile organic compounds (VOCs) emitted by healthy and infested plants. The system was installed inside three separate experimental cages, arranged in parallel to prevent cross-interference in the emission and dispersion of volatiles. In each test, which lasted 24 h, one cage was used as a negative control, containing three *Solanum tuberosum* (potato) plants free of infestation, while the other two cages each contained three plants infested with 25–30 early-stage (L1–L2) *L. decemlineata* larvae, obtained from a colony kept in the laboratory at 25°C and fed with fresh potato leaves. This experimental design ensured that the detection system was exposed to both the VOCs emitted naturally by healthy plants and those generated in response to pest attack. A total of seven trials

Table 1
Sensors integrated in the optical array.

Sensing material	Dye	Support	mg dye / g support
S1	1	UVM-7	1.94
S2	2	UVM-7	1.38
S3	3	UVM-7	2.35
S4	4	UVM-7	1.77
S5	5	Alumina	2.23
S6	6	Alumina	1.98
S7	7	Alumina	0.57
S8	8	Alumina	0.59
S9	9	Silica	0.54
S10	2	Silica	0.86
S11	10	Silica	1.13
S12	11	Silica	0.45

were carried out under the same experimental protocol, each consisting of three cages (one control and two infested with *L. decemlineata*), to evaluate measurement reproducibility. Each trial was carried out on a different day using separate plants and insect groups, constituting independent biological replicates and resulting in a total of 21 measurements per experimental condition.

Images of the optical sensors were captured both before and after the assay using a Canon EOS R50 camera and a lightbox with controlled illumination, ensuring consistent image acquisition conditions. RGB coordinates were extracted from the acquired images using a custom Python-based software developed specifically for the automated retrieval of these values. Subsequently, the ΔE parameter (Eq. 1) was calculated as a metric to quantify the chromatic variations detected by the sensors. This parameter, derived from the differences between the RGB coordinates before and after exposure, provides a more precise and synthetic assessment of colour changes, outperforming the individual analysis of each RGB component in interpreting the responses of the sensing system.

$$\Delta \mathrm{E} = \sqrt{(R_1 - R_0)^2 + (G_1 - G_0)^2 + (B_1 - B_0)^2} \quad (1)$$

2.2. Pattern recognition and data modelling

Principal Component Analysis (PCA) was applied using IBM SPSS Statistics software, version 28.0.1.1 (IBM Corp., Armonk, NY, USA), using the Varimax rotation method as an unsupervised exploratory technique to assess the intrinsic structure of the data and visualise possible clustering patterns between infested and non-infested samples. The sensor responses were autoscaled, and the components with the highest explained variance were retained for interpretation, allowing the evaluation of class separation and identification of dominant trends within the multivariate data set.

Partial Least Squares Discriminant Analysis (PLS-DA) was used as a supervised classification method to model the relationship between the optical sensor responses and the categorical response variable corresponding to the presence or absence of *L. decemlineata*. The PLS-DA models were constructed using a linear discriminant approach in the R environment using the 'mdatools' library. Previously, the signals obtained from the sensors were auto scaled (centred on the mean and scaled by the standard deviation) to normalise variable magnitudes and ensure comparability between magnitudes with different scales. The optimal number of latent variables was determined by minimising the classification error during one-out-of-one cross-validation (LOO-CV). Model performance was evaluated in terms of recall (TPR), TNR, precision, F-score and accuracy.

The Artificial Neural Network (ANN) was implemented in the R environment using the 'nnet' and 'NeuralNetTools' packages. Different neural architectures were evaluated, varying the number of neurons in the hidden layer between 1 and 5, to optimise the model fit. To develop the model the dataset was randomly divided into a calibration set (two-thirds of the samples) and an independent validation set (one-third of the samples), ensuring complete separation between training and validation data. The final ANN architecture was selected based on its classification performance on the validation set. Model performance was evaluated in terms of accuracy, 95% CI, p-value, Kappa, sensitivity, specificity and balanced accuracy.

2.3. Model performance evaluation

To evaluate the performance of the supervised classification models (PLS-DA and ANN), a set of standard metrics was used to provide a comprehensive assessment of their predictive ability. Accuracy represents the proportion of correctly classified samples out of the total number of samples, while precision indicates the proportion of true positives among all predicted positives, reflecting the reliability of positive predictions. Recall (sensitivity, true positive rate, TPR) measures the proportion of correctly identified true positives, evaluating the model's ability to detect infested samples. Conversely, specificity (true negative rate, TNR) represents the proportion of correctly classified true negatives, indicating the model's ability to identify non-infested samples.

The F-score provides the harmonic mean between precision and recall, summarising the balance between sensitivity and predictive reliability. The Kappa coefficient quantifies the agreement between predicted and observed classifications, adjusted for random agreement. Balanced accuracy, calculated as the average between sensitivity and specificity, is particularly useful when class distribution are unbalanced. Finally, the 95% confidence interval (95% CI) and p-value were used to assess the statistical robustness and reliability of the classification accuracy.

3. Results and discussion

3.1. Optical sensor array system for detection of L. decemlineata larvae

The plant-insect interaction triggers complex biochemical responses that depend on the type of attacker and the feeding behaviour of the insect. In the case of *L. decemlineata*, a chewing herbivore, potato plants exhibit differential emission patterns of volatile organic compounds, resulting from specific metabolic pathways such as the lipoxygenase pathway, in which jasmonic acid and its derivatives play a central role in defence responses[1,26]. This volatile emission is dynamic and highly dependent on multiple factors, including the physiological state of the plant, the presence of diseases and environmental conditions such as temperature [2]. VOCs released after attack by *L. decemlineata* include green leaf alcohols and aldehydes such as (Z)-3-hexen-1-ol, (E)-2-hexenal and (Z)-3-hexenyl acetate, terpenoids such as linalool, β-myrcene and caryophyllene, and other compounds such as phenylethanol [27].

In this context, a portable and colorimetric optical sensor system has been developed that stands out for being low-cost, visually interpretable, and suitable for early pest detection, aimed at the early detection of *L. decemlineata* on potato plants. Designed with future direct field application in mind, this system aims to provide farmers with a simple but effective tool for real-time monitoring of the pest. Its operation is based on colour changes upon exposure to VOCs, in this case the volatile signature associated with insect attack. By overcoming the limitations of conventional methods - often labour-intensive and non-portable - this approach represents a significant advance towards more efficient, sustainable and non-invasive integrated pest management.

The system incorporates a chromogenic array composed of twelve sensing units (Fig. 1) with diverse chemical and optical properties to obtain different responses to the VOCs fingerprint. To facilitate handling, modulate the dye response and enhance the stability of the sensors, the dyes were supported on three inorganic materials: mesoporous silica UVM-7, aluminium oxide, and silica. UVM-7 silica is particularly notable for its high specific surface area (~1200 m^2/g) and

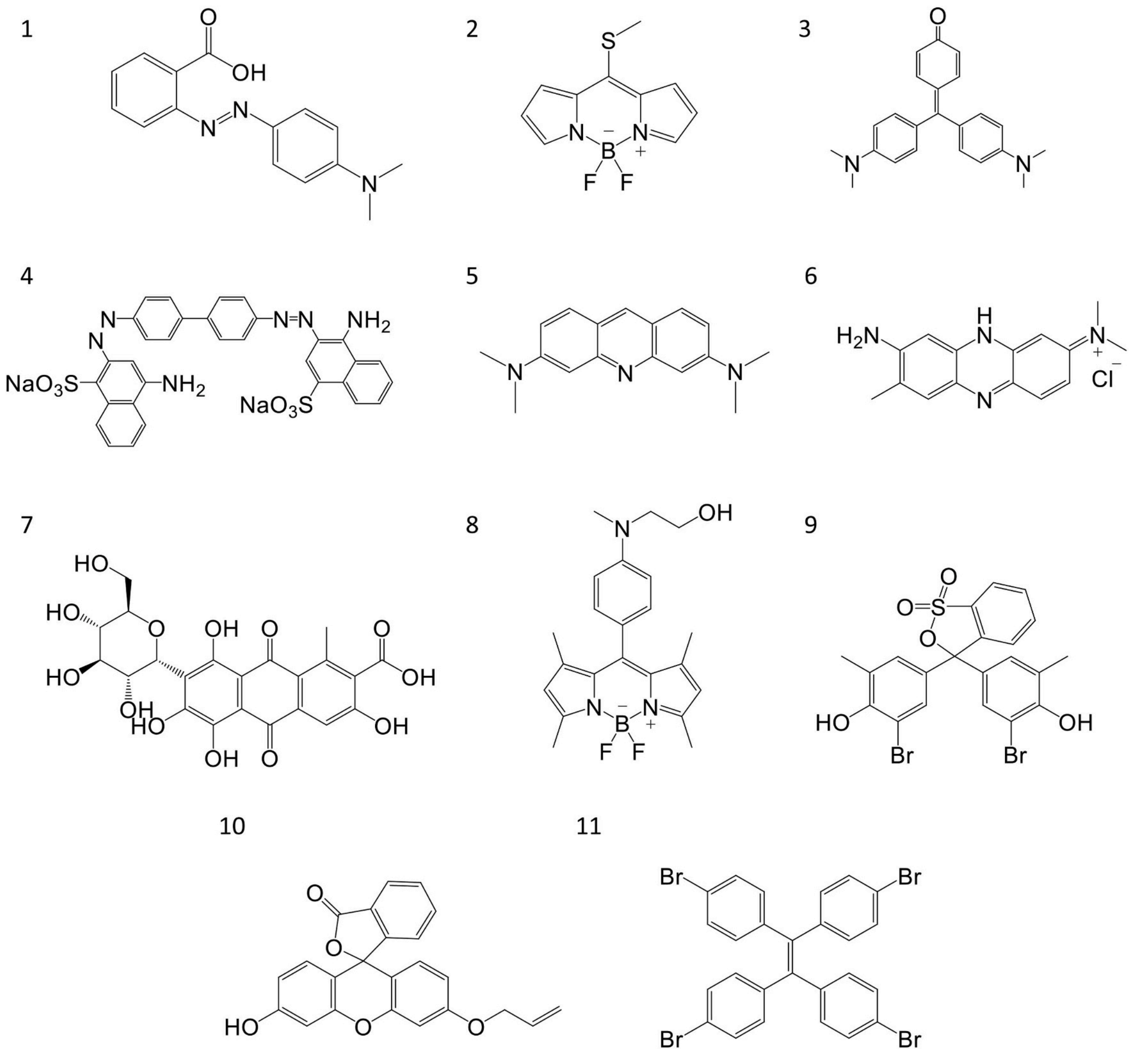

Fig. 1. Chemical structures of molecular indicators used in the optical array.

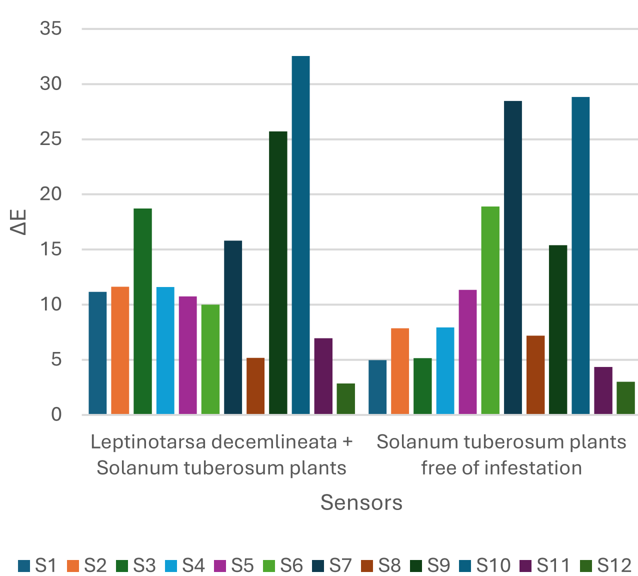

Fig. 2. Overview of the optical response fingerprint generated by the sensory array in *Solanum tuberosum* plants infested by *L. decemlineata*, compared to the spectral profile recorded in non-infested plants.

bimodal porous structure (2 and 40 nm), features that facilitate the adsorption and diffusion of volatile compounds, thereby significantly enhancing the system's sensitivity [28,29]. This combination of sensor array and structural support represents a promising platform for the implementation of early-warning systems within integrated pest management strategies.

3.2. Response patterns to *L. decemlineata*-related volatiles

The performance of the optical system was evaluated through *in vitro* assays, in which the colorimetric array was exposed to *S. tuberosum* plants infested with *L. decemlineata* as well as to non-infested control plants, under controlled experimental conditions. Since both infested

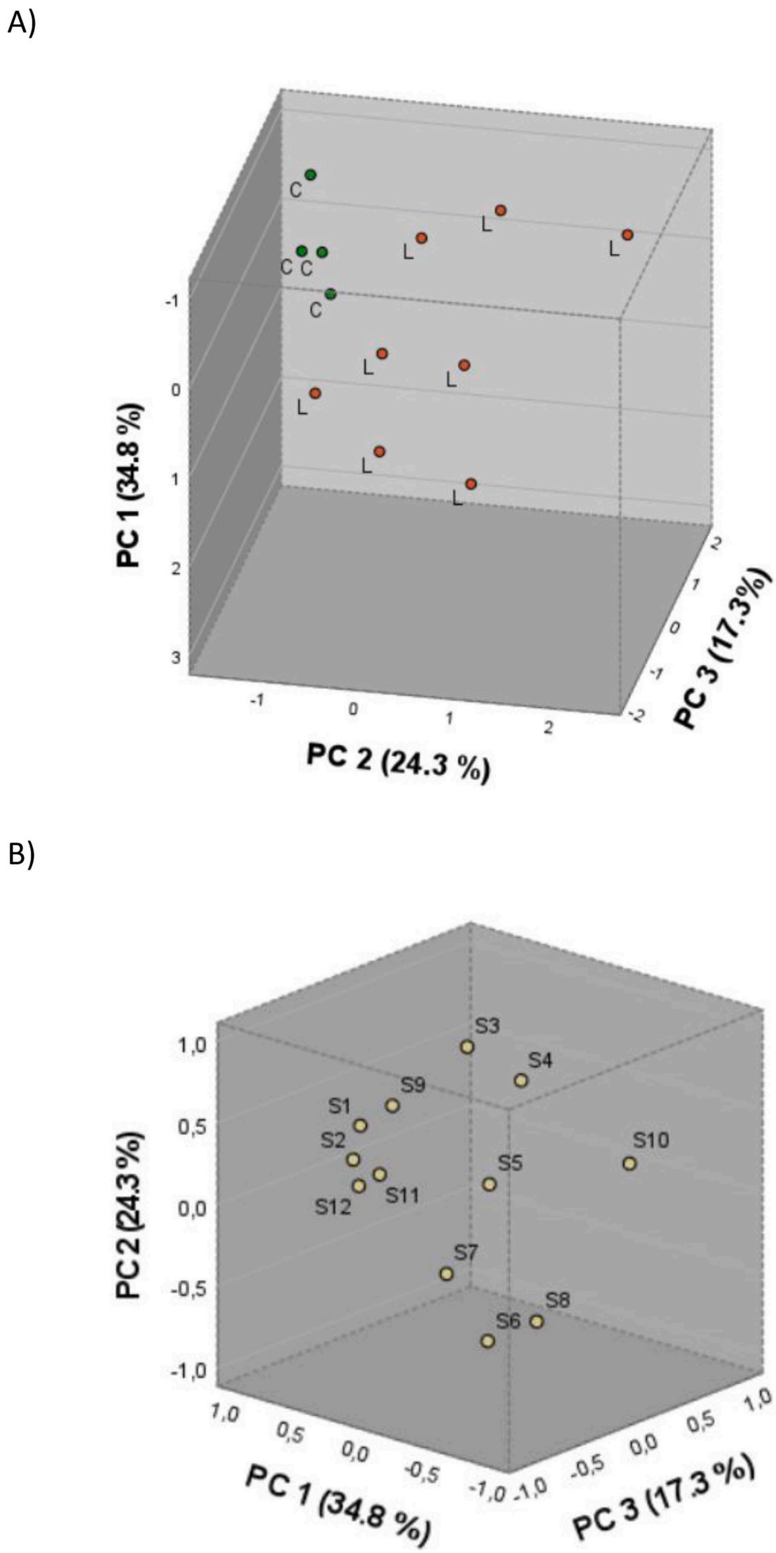

Fig. 3. A) Principal Component Analysis (PCA) scores graphic show the separation between the two experimental groups: plants infested by *L. decemlineata* (L) and non-infested plants (C). B) Loading plot of the 12 optical sensors on the first three main components.

replicas showed highly comparable sensor response patterns, their data were combined to obtain a representative infestation profile. The spectral signals recorded by the sensors under both conditions were analysed to identify response patterns related to the emission of volatile compounds induced by the presence of the pest. Fig. 2 displays the relative response profiles of the sensors, revealing notable differences between infested and non-infested samples. These variations reflect the sensitivity of the colorimetric array to changes in the volatile composition of the environment caused by the pest attack.

To reduce the dimensionality of the data and facilitate interpretation, PCA was applied to the full set of optical responses. The projection of the data in the multivariate space defined by the first three principal components (PC1, PC2, and PC3) enabled a clear visual separation between the experimental groups (Fig. 3A). In this analysis, the samples from the infestation group ("L") were distinctly positioned from the control group ("C"), particularly along the axis defined by the first principal component (PC1), highlighting its relevance as a discriminant variable. The dominant contribution of PC1 suggests that the main source of variability is associated with changes in VOCs typically induced by herbivory, such as green leaf volatiles and terpenoids, which are known to be emitted by potato plants in response to attack by *L. decemlineata*. It is noteworthy that although the samples in group "L" exhibit greater dispersion in the multivariate space, they do not overlap with the control samples. This increased variability may be attributed to factors inherent to the infestation dynamics, such as the variable intensity of attack or individual differences in volatile emission by the affected plants. Nonetheless, this variability does not compromise the system's discriminative capacity, which proves to be robust under less homogeneous biological conditions and shows a strong potential to accurately identify the presence of *L. decemlineata* through the combined analysis of sensor signals.

The analysis of the loadings obtained from the PCA allowed us to identify the sensors with the greatest relevance in differentiating between infested and non-infested conditions (Fig. 3B). In the three-dimensional space defined by the first three principal components (PC1, PC2, and PC3), a clear differentiation between the sensors can be observed based on their behaviour in response to the volatile organic compounds emitted by the plants. Sensors S6, S7, S8 and S10 showed greater dispersion, mainly along the PC1 and PC3 axes, indicating a more sensitive and differentiated response to the volatile compounds associated with *L. decemlineata* infestation. Their greater distance from the origin reflects a greater contribution to the total variance explained by the model. In contrast, sensors S1, S2, S9, S11 and S12 are grouped around the origin, suggesting more homogeneous and less condition-dependent responses. Overall, the distribution observed in the three main components indicates that the system variability is not concentrated on a single PC but rather results from the combined interaction of various chemical-optical dimensions of the sensory array. Furthermore, the joint analysis of PCA distribution and the composition of the sensor array revealed a marked influence of the inorganic support material on the sensory response. Silica-based sensors tended to cluster together, indicating more homogeneous responses, with the notable exception of S10. In contrast, alumina-supported sensors exhibited broader dispersion, which may be linked to lower sensitivity to volatiles. Sensors supported on UVM-7 displayed moderate dispersion and relatively uniform behaviour. Furthermore, the comparison between sensors incorporating the same dye but different supports, such as S2 (UVM-7) and S10 (silica), revealed different response patterns, highlighting the key role of the inorganic support in modulating the optical signal and in determining the overall effectiveness of the array for detecting the presence of the phytophagous insect.

3.3. PLS-DA modelling and classification analysis

To evaluate the discriminative capacity of the optical sensor-based detection system, PLS-DA was employed, a technique widely used due to its effectiveness for classification problems. For model development, the full set of sensors (n = 12) was used, enabling comprehensive capture of the chemical response generated by the interaction between the volatile compounds from the samples and the sensors.

The PLS-DA model was constructed using four latent variables, selected based on their cumulative ability to explain the variance in both the independent variables (X) and the categorical response variable (Y). This number of components was optimal to maximize class discrimination without overfitting, as validated through a leave-one-out cross-validation scheme.

The results demonstrated excellent classification performance. In both calibration and cross-validation phases, the model achieved complete discrimination between samples with (Yes) and without (No) the presence of *L. decemlineata*. All evaluated performance metrics — accuracy, sensitivity (TPR), specificity (TNR), precision, and F-score — reached a value of 1.0, indicating error-free classification under the evaluated experimental conditions (Table 2). This complete class separation highlights the high discriminatory of the sensing system and supports its potential as a robust, non-invasive tool for the early detection of agricultural pests.

These results should be interpreted in the context of the controlled experimental design and the relatively limited size of the dataset. Under laboratory conditions, where the volatile profiles of infested and non-infested plants are chemically well differentiated, it is possible to achieve complete class separation even with a limited number of samples. In this study, the clear discrimination already observed in the unsupervised PCA supports the existence of chemical differences between the two conditions, facilitating error-free classification using supervised models. Therefore, the excellent performance observed would reflect the high signal-to-noise ratio of the system rather than artefacts derived from model overfitting.

However, the potential risk of overfitting associated with the limited sample size was considered. To mitigate this, the model was evaluated using a leave-one-out cross-validation scheme, which yielded results fully consistent with calibration outcomes. Likewise, the number of latent variables was restricted to four components, selected based on their cumulative explanatory power, which helped to ensure an adequate balance between the model's discriminatory power and robustness.

Regarding sensor influence on the PLS-DA model, the results presented in Table 4 show that sensors S1 and S6 were the most relevant of the set, with importance values of 0.47 and 0.48, respectively. This higher contribution could be likely associated with a combination of factors, including the physicochemical properties of their support materials, which may enhance VOC adsorption, as well as the intrinsic affinity between the dyes and specific volatile compounds emitted by infested plants. Consequently, the strong discrimination achieved by the model reflects chemically meaningful sensor-VOC interactions, rather than arbitrary statistical effects.

Sensor S1 (supported on UVM-7) and sensor S6 (supported on alumina), stand out not only for their contribution to the model, but also for the structural properties of their support materials. The high surface area and ordered mesoporousness of UVM-7 favours the adsorption and diffusion of VOCs, while the basic and polar nature of alumina enhances chemical interactions with functionalised dyes.

Intermediate contributions were also observed in sensors S4, S8, and

Table 2
Summary of PLS-DA (cross validation (CV) and calibration (Cal)).

	L. decemlineata	TPR (Recall)	TNR	Precision	F-score	Accuracy
Cal	No	1.000	1.000	1.000	1.000	1.000
	Yes	1.000	1.000	1.000	1.000	1.000
CV	No	1.000	1.000	1.000	1.000	1.000
	Yes	1.000	1.000	1.000	1.000	1.000

S12, which complement the behaviour of the sensory array and strengthen the model's overall classification capacity. Taken together, these results confirm that the combination of UVM-7, alumina, and silica supports, together with the dyes synthesised in the laboratory, enhances the optical response and improves the system's discriminatory capacity. This synergy between material design and chemometric modelling reinforces the overall performance of the device, consolidating its potential as an advanced tool for the early detection and field monitoring of *L. decemlineata*.

3.4. Evaluating Neural Network accuracy for pest detection

In the present study, in addition to PLS-DA, ANN was employed as an advanced statistical approaches for modelling complex data. Although both methods share the goal of classification, they differ significantly in their architecture and in the way they capture relationships between variables. ANNs, even with relatively simple architectures, exhibit a high capacity to model non-linear relationships and detect complex patterns in data; this ability is especially relevant in biological and agricultural systems, where analytical signals can exhibit high variability. The ANN was applied to discriminate between the presence and absence of the pest, achieving remarkable predictive performance in terms of accuracy.

Table 3 shows the associated diagnostic metrics, as well as a summary of the overall model performance. The optimal model was obtained using a single hidden layer, achieving an overall accuracy of 1.0 and a Kappa coefficient of 1.0, reflecting a perfect match between model predictions and observed values, after correcting for the effect of chance. Nevertheless, the statistical robustness of these results must be considered in light of the limited number of samples available for independent validation, these results show a promising performance of ANN for this purpose. Likewise, the model was able to correctly identify all true positives and negatives, with sensitivity and specificity values equal to 1.00. However, the p-value associated with the comparison with the No Information Rate was slightly higher than 0.05, although close to this threshold. Despite the small sample size, the ANN model showed no signs of over-fitting, which was verified by the fact that, during cross-validation, the model predictions were in complete agreement with the real data.

No divergence was observed between training and validation performance, and model predictions remained stable during cross-validation. To minimise overfitting, simple network architectures were deliberately selected, employing a single hidden layer and a small number of neurons. Although the p-value associated with the comparison with the absence of information rate was slightly higher than the conventional threshold of 0.05, this result is attributed to the small size of the dataset and not to model instability. Overall, the ANN results showed no evidence of overfitting.

As shown in Table 4, sensors S6 (0.32), S3 (0.19) and S1 (0.18) showed the highest relevance within the model according to Garson's method, reflecting their high sensitivity to VOC variations associated with the presence of *L. decemlineata*. The combination of sensors S1 and S3, supported on UVM-7, with the alumina-based sensor S6, made the most significant contribution, indicating that certain properties of the support material can enhance the captured signal.

The UVM-7, with its high surface area and ordered mesopores, facilitates the capture and transport of VOCs to the active sites of the sensor, while alumina, due to its polar nature, intensifies interactions with functionalised dyes, increasing the stability and amplitude of the optical response. This pattern suggests that the complementarity between supports with different textural and chemical characteristics helps the neural model to more accurately identify the non-linear relationships between optical signals and the presence of the pest.

Table 4
Relative contribution of sensors in PLS-DA and ANN models.

Sensor	Contribution PLS-DA	Contribution ANN
S1	0.47	0.18
S2	0.07	0.04
S3	0.13	0.19
S4	0.16	0.01
S5	0.10	0.02
S6	0.48	0.32
S7	0.12	0.05
S8	0.18	0.03
S9	0.15	0.06
S10	0.08	0.05
S11	0.10	0.05
S12	0.19	0.06

Silica-based sensors showed lower significance values (<0.1), indicating a smaller contribution to ANN classification, possibly due to their lower affinity with the analytes or lower variability in their response to infestation. Overall, these results reflect consistency between the patterns observed in the ANN and PLS-DA models, highlighting the combined influence of the substrate and dye on the system's response and confirming the key role of UVM-7 and alumina-based sensors in the early detection of *L. decemlineata*. The consistency observed between the sensors identified as relevant by PLS-DA and ANN reinforces the robustness of the system and indicates that classification performance is based on stable and reproducible sensor responses rather than model-specific artefacts.

3.5. System performance in relation to detection techniques reported in the literature

The results obtained confirm that the optical system developed is a robust alternative to the detection methodologies currently reported for *L. decemlineata*. Unlike molecular techniques such as PCR and qPCR, which require DNA extraction and controlled laboratory conditions [30], the proposed tool allows for rapid, non-invasive *in situ* detection, significantly reducing analysis times and operating costs associated with field monitoring. Furthermore, the optical system does not depend on biological material or genetic processing stages, as is the case with RNA interference-based methods [31,32], making the developed tool more suitable for routine applications in agricultural settings.

About remote sensing methodologies, although hyperspectral sensors and multispectral cameras mounted on drones have proven highly effective in identifying plant stress and pest-induced defoliation [8,9], their implementation often involves high technological costs, specialised data processing and logistical limitations in the continuous monitoring of large areas. In contrast, the optical system developed offers a portable, low-cost solution capable of generating real-time responses based on direct interaction with the VOCs emitted by the pest. This feature gives it a significant advantage in early detection, allowing the presence of *L. decemlineata* to be identified before visible damage to the crop becomes apparent.

The combination of the optical signal (colour change) with multivariate analyses (PLS-DA or ANN) showed highly robust performance in the generation of the models for the discrimination between infested and non-infested plants. This analytical approach places the system within

Table 3
Performance evaluation of the neural network-based classification model: statistical validation parameters.

Accuracy	95 % CI	P-Value [Acc>NIR]	Kappa	Sensitivity (Recall)	Specificity	Balanced Accuracy
1.00	(0.3976, 1)	0.0625	1.00	1.00	1.00	1.00

the framework of intelligent detection tools, with a predictive capacity comparable to that of electronic noses used in the diagnosis of biotic stress, which are also based on the recognition of patterns derived from the profiles of volatile organic compounds [33]. However, the device developed has substantial advantages, notably the direct visualisation of colour changes and its high sensitivity, attributed to the use of dyes synthesised in the laboratory itself, which provides a more specific and robust response to the chemical signals of interest. Likewise, the versatility of the system allows its response to be adjusted to different environmental conditions and different types of biotic stress, maintaining high stability, reproducibility and adaptability to variable detection scenarios.

Overall, the performance of the optical system developed demonstrates its potential as a complementary or substitute tool for conventional agricultural pest detection techniques. Its low cost, simplicity of use, portability and real-time response capability make it a viable option for integrated monitoring programmes for *L. decemlineata*, contributing to the development of more sustainable control strategies that are less dependent on chemical inputs.

In this context, future work should focus on validating the proposed optical assembly under real field conditions, where environmental variability (temperature, humidity, and light) can influence both VOC emissions and sensor response. It will also be necessary to extend the study to more extensive and heterogeneous data sets, including different potato cultivars, infestation levels and phenological stages, to evaluate the robustness and generalisability of the system. Finally, evaluating its specificity in relation to other plant stresses, both biotic and abiotic, together with its integration into a portable platform with automated data acquisition and real-time analysis, will consolidate its applicability within integrated pest management and precision agriculture strategies.

Conclusions

A portable optical array composed of 12 chemical sensors based on dyes supported in inorganic materials can be an efficient tool for the detection of *L. decemlineata on S. tuberosum* plants. Multivariate analysis PLS-DA and ANN revealed an outstanding discriminative ability of the system, allowing a clear and accurate separation between infested and non-infested plants, with optimal classification metrics. Sensors S1 and S6 show the greatest influence on the PLS-DA and ANN models, demonstrating their high sensitivity to volatile compounds associated with the infestation. The ANN showed high classification performance, with no evidence of over-fitting, although this performance could be influenced by sample size. Among the main advantages of the system are its portability, ease of use and direct applicability in the field, requiring only a camera and a computer for its operation. In addition, it is a non-invasive technique, which allows for rapid diagnosis without affecting the integrity of the crop. The results obtained support the potential use of this technology as an effective and selective tool for the early detection of *L. decemlineata*, favouring its integration in integrated pest management strategies in potato crops.

Funding sources

This research was funded by the AGROALNEXT/2022/065 grant from Conselleria d'Innovació, Universitats, Ciència i Societat Digital (Generalitat Valenciana, Spain) and MCIN, NextGenerationEU (PRTR-C17.I1) Funds.

Ethical statement

This research does not involve research with human or personal data. We have fulfilled all the ethical requirements.

CRediT authorship contribution statement

Sheila Sánchez-Artero: Investigation. **Inmaculada García-Robles:** Investigation. **M. José López-Galiano:** Investigation. **Carolina Rausell:** Investigation. **Pablo Gaviña:** Investigation. **Pedro Amorós:** Investigation. **Jose Vicente Ros-Lis:** Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

[1] V. Gosset, N. Harmel, C. Göbel, F. Francis, E. Haubruge, J.P. Wathelet, et al., Attacks by a piercing-sucking insect (*Myzus persicae Sultzer*) or a chewing insect (*Leptinotarsa decemlineata Say*) on potato plants (*Solanum tuberosum L.*) induce differential changes in volatile compound release and oxylipin synthesis, J. Exp. Bot. 60 (4) (2009) 1231–1240, https://doi.org/10.1093/jxb/erp015.

[2] D. Rajabaskar, Y. Wu, N.A. Bosque-Pérez, SD. Eigenbrode, Dynamics of *Myzus persicae* arrestment by volatiles from Potato leafroll virus-infected potato plants during disease progression, Entomol. Exp. Appl. 148 (2) (2013) 172–181, https://doi.org/10.1111/eea.12087.

[3] V.M. Izzo, Y.H. Chen, S.D. Schoville, C. Wang, DJ. Hawthorne, Origin of pest lineages of the colorado potato beetle (coleoptera: Chrysomelidae), J. Econ. Entomol. 111 (2) (2018) 868–878, https://doi.org/10.1093/jee/tox367.

[4] Y.H. Chen, Z.P. Cohen, E.M. Bueno, B.M. Christensen, SD. Schoville, Rapid evolution of insecticide resistance in the Colorado potato beetle, *Leptinotarsa decemlineata*, Curr. Opin. Insect Sci. 55 (2023) 101000, https://doi.org/10.1016/j.cois.2022.101000.

[5] A. Robles-Fort, S. Pescador-Dionisio, I. García-Robles, V. Sentandreu, A. C. Martínez-Ramírez, M.D. Real, et al., Unveiling gene expression regulation of the *Bacillus thuringiensis* cry3aa toxin receptor adam10 by the potato dietary mir171 in colorado potato beetle, Pest. Manage Sci. 78 (9) (2022) 3760–3768, https://doi.org/10.1002/ps.6743.

[6] I. García-Robles, J. De Loma, M. Capilla, I. Roger, P. Boix-Montesinos, P. Carrión, et al., Proteomic insights into the immune response of the Colorado potato beetle larvae challenged with *Bacillus thuringiensis*, Dev. Comp. Immunol. 104 (2020) 103525, https://doi.org/10.1016/j.dci.2019.103525.

[7] M. Kadoić Balaško, K.M. Mikac, R. Bažok, D. Lemic, Modern techniques in Colorado potato beetle (*Leptinotarsa decemlineata* Say) control and resistance management: history review and future perspectives, Insects 11 (9) (2020) 581, https://doi.org/10.3390/insects11090581.

[8] F.H. Iost Filho, W.B. Heldens, Z. Kong, E.S. de Lange, Drones: innovative technology for use in precision pest management, J. Econ. Entomol. 113 (1) (2020) 1–25, https://doi.org/10.1093/jee/toz268.

[9] A. Terentev, V. Dolzhenko, A. Fedotov, D. Eremenko, Current state of hyperspectral remote sensing for early plant disease detection: a review, Sensors 22 (3) (2022) 757, https://doi.org/10.3390/s22030757.

[10] AK. Mahlein, Plant disease detection by imaging sensors – parallels and specific demands for precision agriculture and plant phenotyping, Plant Dis. 100 (2) (2016) 241–251, https://doi.org/10.1094/PDIS-03-15-0340-FE.

[11] A. Brosset, JD. Blande, Volatile-mediated plant-plant interactions: volatile organic compounds as modulators of receiver plant defence, growth, and reproduction, J. Exp. Bot. 73 (2) (2022) 511–528, https://doi.org/10.1093/jxb/erab487.

[12] A. Rani, A. Rana, R.K. Dhaka, A.P. Singh, M. Chahar, S. Singh, et al., Bacterial volatile organic compounds as biopesticides, growth promoters and plant-defense elicitors: current understanding and future scope, Biotechnol. Adv. 63 (2023) 108078, https://doi.org/10.1016/j.biotechadv.2022.108078.

[13] L. Hunziker, D. Bönisch, U. Groenhagen, A. Bailly, S. Schulz, L. Weisskopf, Pseudomonas strains naturally associated with potato plants produce volatiles with high potential for inhibition of *Phytophthora infestans*, Appl. Environ. Microbiol. 81 (3) (2015) 821–830, https://doi.org/10.1128/AEM.02999-14.

[14] R. Caparros Megido, L. De Backer, R. Ettaïb, Y. Brostaux, M.L. Fauconnier, P. Delaplace, et al., Role of larval host plant experience and solanaceous plant volatile emissions in *Tuta absoluta* (Lepidoptera: Gelechiidae) host finding behavior, Arth.-Plant Int. 8 (4) (2014) 293–304, https://doi.org/10.1007/s11829-014-9315-2.

[15] A. Sanaeifar, H. ZakiDizaji, A. Jafari, M. De la Guardia, Early detection of contamination and defect in foodstuffs by electronic nose: a review, TrAC Trends Anal. Chem. 97 (2017) 257–271, https://doi.org/10.1016/j.trac.2017.09.014.

[16] W. Wojnowski, T. Majchrzak, T. Dymerski, J. Gębicki, J. Namieśnik, Electronic noses: Powerful tools in meat quality assessment, Meat. Sci. 131 (2017) 119–131, https://doi.org/10.1016/j.meatsci.2017.04.240.

[17] S. Fuentes, E. Tongson, R.R. Unnithan, CG. Viejo, Early detection of aphid infestation and insect-plant interaction assessment in wheat using a low-cost electronic nose (E-Nose), near-infrared spectroscopy and machine learning modeling, Sensors 21 (17) (2021) 5948, https://doi.org/10.3390/s21175948.

[18] A.D. Wilson, M. Baietto, Applications and advances in electronic-nose technologies, Sensors 9 (7) (2009) 5099–5148, https://doi.org/10.3390/s90705099.

[19] A. Wilson, Diverse applications of electronic-nose technologies in agriculture and forestry, Sensors 13 (2) (2013) 2295–2348, https://doi.org/10.3390/s130202295.

[20] J. Laothawornkitkul, J.P. Moore, J.E. Taylor, M. Possell, T.D. Gibson, C.N. Hewitt, et al., Discrimination of plant volatile signatures by an electronic nose: a potential technology for plant pest and disease monitoring, Environ. Sci. Technol. 42 (22) (2008) 8433–8439.

[21] T. Seesaard, N. Goel, M. Kumar, C. Wongchoosuk, Advances in gas sensors and electronic nose technologies for agricultural cycle applications, Comput. Electron. Agric. 193 (2022) 106673, https://doi.org/10.1016/j.compag.2021.106673.

[22] S. Sánchez-Artero, L. Roca-Perez, A. Soriano-Asensi, R. Boluda, E. Fernández-Gómez, P. Amorós, et al., Application of an optoelectronic nose for the monitoring and modeling of composting dynamics, Microchem J. 216 (2025) 114762, https://doi.org/10.1016/j.microc.2025.114762.

[23] S. Sánchez-Artero, C. Montesinos, P. Amorós, JV. Ros-Lis, Development of an optoelectronic tool for the detection of Cotonet de les Valls in citrus crops, Sens. Actuators B Chem. 448 (2026) 139021, https://doi.org/10.1016/j.snb.2025.139021.

[24] Y. Salinas, V.J Ros-Lis, J.L. Vivancos, R. Martínez-Máñez, M. Dolores Marcos, S. Aucejo, et al., Monitoring of chicken meat freshness by means of a colorimetric sensor array, Analyst 137 (16) (2012) 3635–3643, https://doi.org/10.1039/c2an35211g.

[25] Y. Salinas, J.V. Ros-Lis, J.L. Vivancos, R. Martínez-Máñez, S. Aucejo, N. Herranz, et al., A chromogenic sensor array for boiled marinated turkey freshness monitoring, Sens. Actuators B Chem. 190 (2014) 326–333, https://doi.org/10.1016/j.snb.2013.08.075.

[26] A.M. Lafta, JH. Lorenzen, Influence of High Temperature and reduced irradiance on glycoalkaloid levels in potato leaves, J. Am. Soc. Hortic. Sci. 125 (5) (2000) 563–566.

[27] B. Weißbecker, S. Schütz, A. Klein, H.E. Hummel, Analysis of volatiles emitted by potato plants by means of a Colorado beetle electroantennographic detector, Talanta 44 (12) (1997) 2217–2224, https://doi.org/10.1016/S0039-9140(97)00037-4.

[28] J. Pavel Anzenbacher, P. Lubal, P. Buček, A.M Palacios, E.M. Kozelkova, A practical approach to optical cross-reactive sensor arrays, Chem. Soc. Rev. 39 (10) (2010) 3954–3979, https://doi.org/10.1039/b926220m.

[29] J.E. Haskouri, Zárate DO de, C. Guillem, J. Latorre, M. Caldés, A. Beltrán, et al., Silica-based powders and monoliths with bimodal pore systems, Chem. Commun. (4) (2002) 330–331.

[30] V. Sedláková, P. Vejl, P. Doležal, J. Vašek, D. Čílová, M. Melounová, et al., Detection of sex in adults and larvae of *Leptinotarsa decemlineata* on principle of copy number variation, Sci. Rep. 12 (1) (2022) 4602, https://doi.org/10.1038/s41598-022-08642-x.

[31] Z. Cohen, M.S. Crossley, R.F. Mitchell, P. Engsontia, Y.H. Chen, SD. Schoville, Evolution of chemosensory genes in Colorado potato beetle, *Leptinotarsa decemlineata*, J. Evol. Biol. 37 (1) (2024) 62–75, https://doi.org/10.1093/jeb/voad004.

[32] Z.P. Cohen, K. Brevik, Y.H. Chen, D.J. Hawthorne, B.D. Weibel, SD. Schoville, Elevated rates of positive selection drive the evolution of pestiferousness in the Colorado potato beetle (Leptinotarsa decemlineata, Say), Mol. Ecol. 30 (1) (2021) 237–254.

[33] A. Cellini, S. Blasioli, E. Biondi, A. Bertaccini, I. Braschi, F. Spinelli, Potential applications and limitations of electronic nose devices for plant disease diagnosis, Sensors 17 (11) (2017) 2596, https://doi.org/10.3390/s17112596.