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Volatile Organic Compounds (VOCs) Biomarker-based Early Warning System for *Spodoptera frugiperda* Detection and Monitoring Using an Electronic Nose

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Abstract

The fall armyworm (*Spodoptera frugiperda*) significantly impacts agriculture and the economy. Traditional management methods are often ineffective, as this pest grows rapidly and spreads widely. By the time farmers notice signs of crop damage, extensive harm may have already occurred. There is an urgent need for rapid and accurate detection technologies that are environmentally friendly to enhance agricultural sustainability. Thus, our aim was not to identify any individual VOC compounds; instead, we obtained readings from sensors representing the entire VOC composition released by plants when damaged by these pests. This study developed a real-time monitoring system for fall armyworm outbreaks, with alerts delivered via a smartphone application. We detected VOCs in various types of corn, including maize, sweet corn, and purple corn, under three conditions: healthy controls, infested by fall armyworms, and mechanically damaged. Results show that VOC responses from fall armyworm-infested plants significantly increased, while mechanically damaged plants spiked quickly but then decreased rapidly compared to healthy plants. The Linear SVM model achieved over 93.5% accuracy and an F1-score between 0.88 and 0.93. The system can process and classify corn plant statuses in real-time. This study demonstrates that VOCs may serve as biomarkers for detecting *Spodoptera frugiperd*a. Findings support the development of an early warning system using e-nose technology and SVM algorithms for monitoring and managing pest infestations in their initial stages.

Keywords
Fall armyworm, Volatile organic compounds (VOCs), Real-time monitoring, E-nose, Pest detection

1. Introduction
Corn (*Zea mays*) is one of the most widely cultivated cereal crops globally, serving as a staple food source, animal feed, and a critical ingredient in various industrial products. Due to its adaptability to diverse climates and its high yield potential, corn plays a significant role in food security and agricultural economies (Wang and Hu 2021). Maize accounts for approximately 60% of total corn usage worldwide, serving as a primary ingredient in livestock feed, which supports the rapidly growing demand for protein (USDA 2021). In Thailand, both types of corn play essential roles in the agricultural sector, where maize is crucial for livestock production, and sweet corn cultivation provides income for farmers and supports rural development (Department of Agricultural Extension 2020). These crops are vital for ensuring food security and sustaining livelihoods in both local and global markets.

The fall armyworm (*Spodoptera frugiperda*) has emerged as a significant global agricultural pest, particularly affecting maize and other crops, leading to yield losses of 20% to 50% (Gao et al. 2020). Its economic impact is profound, as it threatens food security and livelihoods for millions of farmers, especially in developing regions

(FAO 2021). The pest's rapid spread from the Americas to Africa and Asia poses ongoing challenges for pest management and exacerbates agricultural instability (Korycinska et al. 2021).

Plants release volatile organic compounds (VOCs) as part of their natural defense mechanisms against herbivores and pathogens. These volatile compounds serve as chemical signals that can warn neighboring plants of imminent threats, inducing a defensive response (Dicke & van Poecke 2002). In addition to herbivore-induced plant VOCs, these compounds can also play a crucial role in attracting natural enemies of herbivores, such as parasitoids and predators, enhancing biological control in agricultural systems (Kessler & Baldwin 2001).

Farmers traditionally manage the fall armyworm through a combination of cultural practices, biological control, and chemical pesticides. Common strategies include crop rotation, intercropping, timely planting, and the use of natural predators such as parasitic wasps (FAO 2021). However, reliance on chemical control can lead to increased production costs and environmental concerns. Recent technological advancements, such as electronic nose (e-nose) technology, offer promising avenues for enhanced detection and management of fall armyworm. E-nose devices can analyze volatile organic compounds emitted by damaged plants or present in the pest's environment, providing early warning signals of infestation. This proactive approach allows for targeted pest management interventions, potentially reducing the need for broad-spectrum pesticide applications and promoting sustainable agricultural practices (Korycinska et al. 2021).

The utilization of electronic nose (e-nose) technology has emerged as a revolutionary tool for detecting plant VOCs associated with pest infestations. E-noses are devices that mimic the human sense of smell, utilizing an array of sensors to identify specific chemical signatures in the air. By analyzing the profile of VOCs emitted by plants under stress, e-noses can provide early detection of pest attacks, including fall armyworm infestations, allowing for timely intervention and more targeted pest management strategies (Fahad et al., 2020). This technology offers a sustainable alternative to conventional pest control methods by reducing chemical pesticide reliance while promoting the health of agroecosystems.

Traditional methods of managing fall armyworm infestations face significant limitations, highlighting an urgent need for rapid and accurate detection technologies that are environmentally friendly to enhance long-term agricultural sustainability. Thus, our research team aims to examine whether a low-cost VOC sensor array can identify odor sources and compositions from plants and insects, as well as its potential application for detecting insects in the field.

1.1 Objectives

We aimed to examine whether VOCs emitted by damaged plants can be used as biological signals to develop a real-time monitoring system for pest detection, with notifications delivered through a smartphone application.

2. Literature Review

The main Challenge in plant pest diagnosis is identifying physical, chemical, and biological changes during the asymptomatic stages. Plants have a broad range of defense mechanisms for combatting infections, attacks by herbivorous insects, and mechanical damage (Choudhary, et al. 2008). Traditional pest monitoring methods mainly rely on visual inspection and manual field surveys, which are time-consuming and often fail to detect infestations at an early stage. As a result, researchers have increasingly focused on sensor-based detection approaches and data analysis techniques for agricultural pest monitoring.

VOCs are increasingly recognized as crucial biomarkers for detecting plant responses to biotic stresses, including herbivore attacks. When plants are subjected to herbivory, they can produce a suite of VOCs that serve various ecological functions, including signaling to neighboring plants or attracting natural enemies of the herbivores (Dicke & van Loon, 2000). Biologically, VOCs are produced by a wide range of physiological processes in many different parts of plant tissues. Plants require a broad range of defense mechanisms to effectively combat attacks by herbivorous insects or mechanical damage (Choudhary et al. 2008). One of the strategies is to emit specific VOCs to battle potential attacks. While some protective VOCs are always emitted, others are induced only in response to herbivore feeding (Frost et al. 2008). The response of plants to insect herbivores like *Spodoptera frugiperda* typically involves the release of specific VOCs, such as green leaf volatiles, terpenoids, and phenolic compounds (Turlings et al. 1995; Kanchiswamy et al. 2015). Studies have shown that these VOCs can serve as reliable indicators of plant stress, with compounds being correlated with the extent of damage (Aharoni & Keasling, 2008). For instance, *S. frugiperd*a feeding may evoke a characteristic profile of VOCs, which can be monitored to assess plant health and pest pressure (Mafongoya et al. 2020). Recent advances in chromatography and mass spectrometry have allowed for the precise identification and quantification of these VOCs, thereby improving our ability to use them as biomarkers for real-time monitoring of plant health (Pare & Tumlinson 1997).

Considering these developments, e-nose technology has emerged as a powerful tool for detecting pests and assessing plant stress based on VOC emissions. It is well known that e-nose are designed to identify the entire fingerprint of VOCs, but not individual volatile components. E-noses consist of an array of gas sensors that can mimic the olfactory system, providing the ability to detect complex mixtures of VOCs with high sensitivity and specificity (Cui et al. 2018). Several studies have demonstrated the efficacy of e-nose technology in identifying the presence of pests like *S. frugiperda* in agricultural settings. For example, an e-nose system was employed to distinguish between healthy plants and those affected by herbivory, utilizing the unique VOC profiles emitted in response to insect feeding (Pérez et al. 2017). The e-nose's ability to process and analyze odor signatures allows it to offer a rapid and non-invasive means of monitoring plant health and pest presence, making it a promising tool for integrated pest management strategies (Khan et al. 2020). Such technology not only enhances pest detection capabilities but also aids in developing early warning systems that can help farmers make informed decisions regarding pest control measures. Thus, e-nose technology can provide a new platform for plant pest diagnosis.

Furthermore, the application of machine learning (ML) techniques has significantly advanced the analysis of VOC data in pest detection and classification. By utilizing algorithms such as support vector machines, random forests, and neural networks, researchers have been able to develop models that accurately classify and predict plant stress levels based on VOC emissions (Islam et al. 2021). Machine learning enhances traditional analytical methods, providing robust tools to analyze large datasets derived from e-nose outputs. In recent studies, ML algorithms have been trained on VOC profiles associated with healthy and stressed plants due to *S. frugiperda* feeding (Rivas et al. 2021). These models have demonstrated high accuracy in classifying stress levels, thereby paving the way for developing predictive analytics in agriculture. The integration of machine learning with e-nose technology enables the construction of sophisticated early warning systems that can provide real-time monitoring and alerts related to pest-induced plant stress, optimizing pest management strategies and improving crop resilience (Yuan et al. 2022).

3. Methods

3.1. Insects and plants

Spodoptera frugiperda larvae were collected from corn fields in Mae Rim District, Chiang Mai, Thailand. The insects were reared for one life cycle, after that larva were reared individually in plastic cups (2 cc) with lids on a piece of baby corn. Adult moths were fed with 10 % honey solution via a cotton wick. Eggs laid by adults were transferred to separate rearing containers (30 × 20 ×50 cm) to ensure proper development.

Zea mays (Maize, Pacific 999, Pacific Seeds Thailand Co., Ltd., Thailand; Sweet corn, Chai Tai Co., Ltd., Thailand; Purple corn, Chai Tai Co., Ltd., Thailand). Different corn varieties grew separately. Sowing seeds in seeding trays filled with potting soil for one week. Then, the seedings were carefully grown into plastic pots with a capacity of 10 to 15 liters under greenhouse conditions. Plants were watered twice per week and 46–0- 0 fertilizer (Rabbit Brand, Chai Tai Co., Ltd., Thailand) was applied when seedlings were two weeks old. Seedlings were grown for two to four weeks before being used in experiments.

3.2 E-nose

The e-nose operates with two main systems:

1. Air Conditioning and Clearance System: This system is responsible for adjusting the internal environment of the device's tube or chamber to minimize interference and increase measurement accuracy.

1.1 Air Conditioning System: This component adjusts the air conditions back to baseline values using an SHT31 sensor (Sensirion Co., Ltd., Switzerland).

1.2 Air Clearance System: This subsystem uses a pump to draw air from the sensor chamber through a cannula tube into a filtration unit filled with activated charcoal granules to remove residual volatile compounds.

2. VOCs Collection and Measurement System: This system utilizes a fan to draw air into the system so that it can be delivered to the Grove Multichannel Gas Sensor v2 (Seeed Studio, Seeed Technology Co., Ltd., China), which consists of four gas-sensing channels. Signals from all four sensors were recorded simultaneously. To represent the overall VOC response at each measurement time point, the outputs from the four sensors were combined by calculating the arithmetic mean, and this averaged value was used for subsequent temporal analysis and graphical presentation.The sensor data were transferred to an ESP32 board (Espressif Systems Co., Ltd., China), which collected and prepared the information for analysis by the AI system. Prior to all experimental measurements, the sensors were calibrated with filtered ambient air to establish a baseline resistance (R_0). This blank measurement was repeated before each run to monitor sensor stability. Sensors were allowed to stabilize for at least 5 minutes. Sensor drift and sensitivity were periodically checked using standard VOC vapors. The chamber was flushed with clean air between runs to prevent odor carryover, and identical protocols were applied to all treatments and replicates (Figure 1).

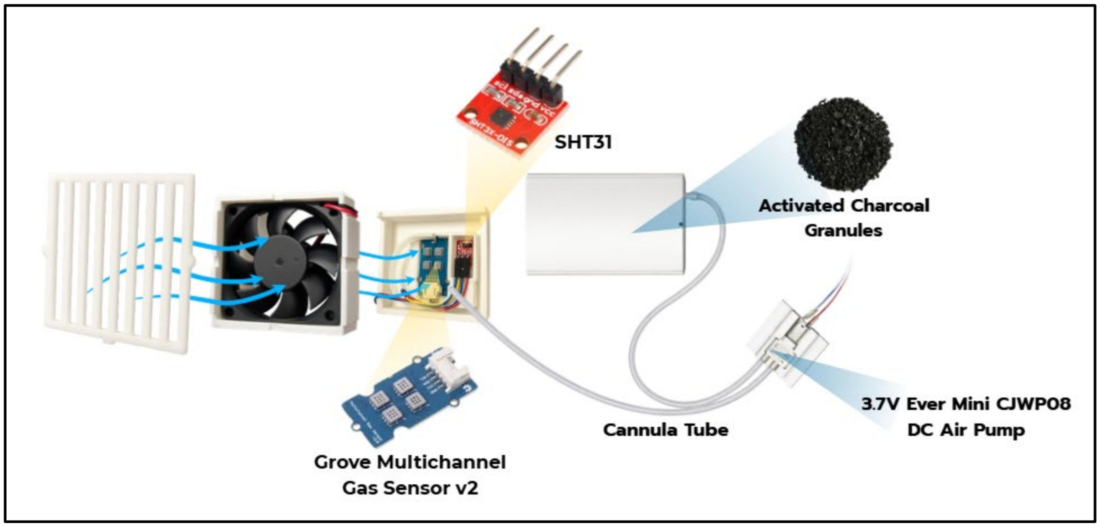

Figure 1. Schematic diagram of the e-nose system setup, illustrating the airflow pathway and main components, including the DC air pump, activated charcoal filter, cannula tube, cooling fan, Grove Multichannel Gas Sensor v2, and the SHT31 temperature and humidity sensor.

3.3 Machine Learning and AI

The device receives data from the sensor and preprocesses the signals before analysis. The collected datasets were cleaned, transformed, and divided into two subsets for model development and evaluation. Selecting an appropriate pattern recognition algorithm is crucial for effectively extracting meaningful information from mixed and noisy sensor signals. In this study, conventional statistical and machine learning methods, including principal component analysis (PCA), linear discriminant analysis (LDA), and support vector machine (SVM), were employed. PCA and LDA play essential roles in recognizing patterns in sensor responses, particularly in scenarios involving multiple data clusters. PCA was used to reduce the dimensionality of the e-nose response data, while LDA enhanced class separability and improved classification accuracy. SVM was applied as a supervised learning algorithm for classification and implemented on the ESP32 board using a pre-trained model suitable for real-time processing. Meanwhile, summarized data and event alerts were transmitted to a Firebase-based server for in-depth analysis and user notification via an application or online system. Firebase also served as a backend for storing historical data, enabling efficient data retrieval for further analysis. After training, the model was evaluated using performance metrics including accuracy, precision, recall, F1-score, and a confusion matrix. Although additional experiments demonstrated that a Random Forest model could achieve very high classification accuracy reaching up to 100% in some datasets further analysis indicated a high risk of overfitting, particularly due to the limited dataset size and strong correlations among VOC features. As a result, Random Forest was excluded to ensure better robustness and generalization to unseen data.

3.4 Notification System via Smartphone Application

This system allows users to receive alerts and notifications directly on their smartphone through a dedicated application. Notifications may include real-time data updates, and alarm for abnormal conditions.

3.5 Statistical Analysis

The analysis of the VOC signal data was conducted using PCA to reduce dimensionality and visualize the data structure. To evaluate whether healthy, insect-infested, and mechanically damaged plants could be differentiated, a one-way Analysis of Similarities (ANOSIM) was performed. Additionally, a Linear Support Vector Machine (Linear SVM) was applied to further classify the corn plants, and confusion matrices were generated to assess the classification performance.

4. Data Collection

Detection of plant VOCs under laboratory and greenhouse conditions

Zea mays plants were divided into three groups: the control group (healthy), infested by fall armyworms group (two third-instar *S. frugiperda* larvae were placed on a two-week-old maize plant), and mechanical damage group (leaves were mechanically damaged by hand).

Data will be collected according to standard protocols, measuring for 7 minutes followed by a 30-minute interval. This process will continue for a total of 3 hours for each experimental condition. The change in the signal will be monitored at 24, 48, and 72 hours after stimulation to study the temporal pattern of VOCs emissions. The plant status classification will be recorded and evaluated by logging time-stamped sensor response values and environmental variables at every measurement point. Group separation will be assessed using LDA, and data structure will be evaluated with SVM. A supervised model will be trained and evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. The detection time and system response (in milliseconds) will be measured from the start of sampling to the end-to-end inference time, repeated under all conditions and for every type of *Zea mays*. Data sets will be varied, and testing will be conducted at least five times for each configuration. The stability of the system will be evaluated under varying environmental conditions by measuring sensor signal changes at different temperatures and humidity levels over a specified timeframe. Signal noise will be assessed, along with feature stability and their impact on the F1-score. We developed and compared AI algorithms for classifying the status of the *Zea mays* plants by performing baseline correction and normalization, followed by feature extraction. The best-performing model will be selected for the development and evaluation of a real-time alert system based on VOCs detection.

5. Results and Discussion

5.1 Detection of Plant VOCs emission

The electronic nose system was able to clearly detect distinct response patterns of VOCs emitted from under different experimental conditions, including the control group (healthy plants), plants infested by the fall armyworm, and plants subjected to mechanical damage. VOC signals collected under laboratory conditions exhibited pronounced differences in both signal patterns and stability, reflecting distinct physiological responses of the plants under each condition.

The control group showed relatively stable VOC signal profiles throughout the measurement period, indicating a low level of stress-related volatile emissions. In contrast, both insect-infested and mechanically damaged plants exhibited signal patterns that were clearly differentiated from the control group, demonstrating the capability of the e-nose system to detect changes in plant status induced by external stress factors.

Structural analysis of the VOC signal data using PCA revealed that the first two principal components (PC1 and PC2) accounted for up to 98.901% of the total variance, indicating a well-defined data structure and effective dimensionality reduction. The distribution of samples in the PC1–PC2 space showed clear separation among the three experimental conditions, with insect-infested plants forming a distinct cluster separated from both the control and mechanically damaged groups (Figure 2, Table 1).

To statistically validate the separation observed in the PCA results, a one-way Analysis of Similarities (ANOSIM) was conducted using Euclidean distances of VOC features. The ANOSIM results demonstrated a statistically significant difference among the three plant conditions ($R = 0.674$, $p = 0.001$; 999 permutations), confirming that the observed separation was not due to random variation. These findings indicate that the e-nose system can effectively capture biological differences between insect-induced damage and non-biological mechanical damage, supporting its use as an initial classification stage for plant status detection (Figure 3).

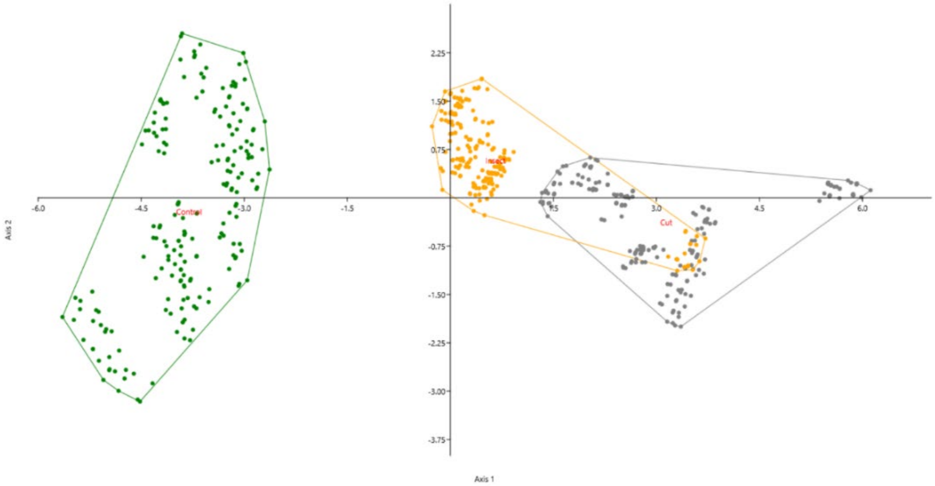

Figure 2. PCA scores plot of volatile organic compound (VOC) responses from *Zea mays* under three experimental conditions: control (green), insect-infested plants by *Spodoptera frugipe*rda (orange), and mechanically damaged plants (gray). Each point represents an individual VOC sample, and convex hulls indicate the distribution range of each treatment group.

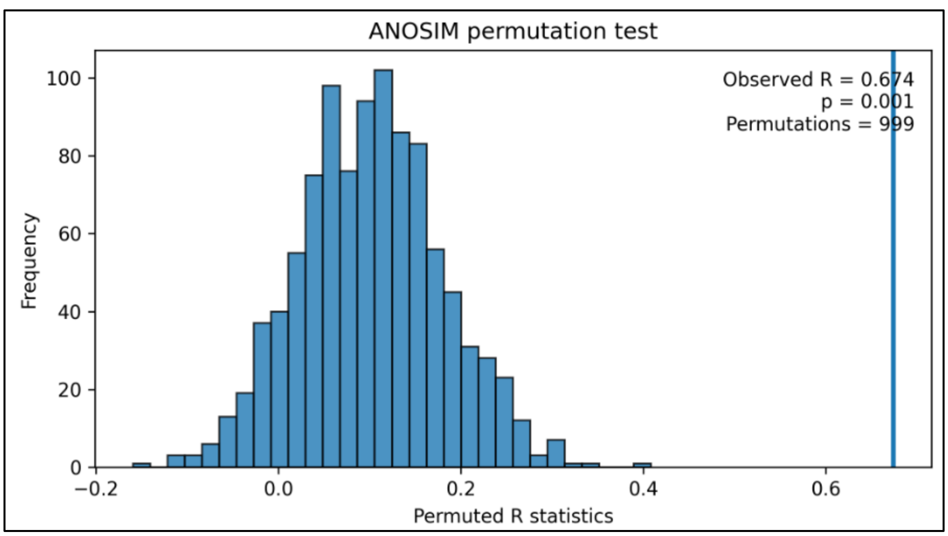

Figure 3. ANOSIM permutation test illustrating the distribution of R statistics obtained from 999 random permutations of group labels. The histogram represents the R values expected under the null hypothesis of no difference among groups. The vertical line indicates the observed R value (R = 0.674), which lies far outside the permutation distribution, demonstrating a statistically significant separation among control, insect-infested, and mechanically damaged plant groups (p = 0.001).

Table 1. Explained variance of principal components derived from PCA

PC	Eigenvalue	Variance %
1	2659.49	98.901
2	27.6056	1.0266
3	13.5264	0.050302
4	0.584883	0.021751

5.2 Temporal dynamics of VOC emissions

Temporal monitoring of VOC emissions revealed time-dependent response patterns following insect infestation and mechanical damage across different maize varieties (Figure 4). Based on the observed trends, plants exposed to *Spodoptera frugiperda* generally exhibited more sustained VOC responses over time, whereas mechanically damaged plants showed relatively rapid and transient changes.

In sweet corn, VOC signals from mechanically damaged plants increased shortly after cutting but gradually declined toward baseline levels during extended monitoring. In contrast, insect-infested plants exhibited more persistent VOC responses, with signal levels remaining comparable or slightly elevated from the early measurement period through 24, 48, and 72 hours. These observations suggest that insect feeding may be associated with prolonged physiological activity compared with short-term wound responses.

A similar trend was observed in anthocyanin-rich (purple) corn. VOC emissions associated with *S. frugiperda* infestation appeared higher during the early and intermediate time points but declined at later stages, particularly at 72 hours, possibly reflecting stress adaptation or changes in defensive metabolism. In contrast, mechanically damaged plants showed weaker and more rapidly diminishing VOC responses, consistent with the transient nature of physical injury.

For maize, both treatments exhibited fluctuations during the early measurement period. However, insect-infested plants tended to maintain more stable VOC profiles over extended time points compared with mechanically damaged plants, particularly beyond 24 hours. This pattern indicates that insect-induced stress may involve ongoing biochemical processes, whereas mechanical damage primarily triggers short-lived volatile release.

Across all varieties, the observed differences in temporal VOC profiles suggest that time-resolved VOC monitoring may provide useful qualitative information for distinguishing biotic stress from physical injury. Nevertheless, quantitative statistical validation was not performed in this study, and future work incorporating larger sample sizes and time-resolved statistical analysis is required to confirm these temporal patterns.

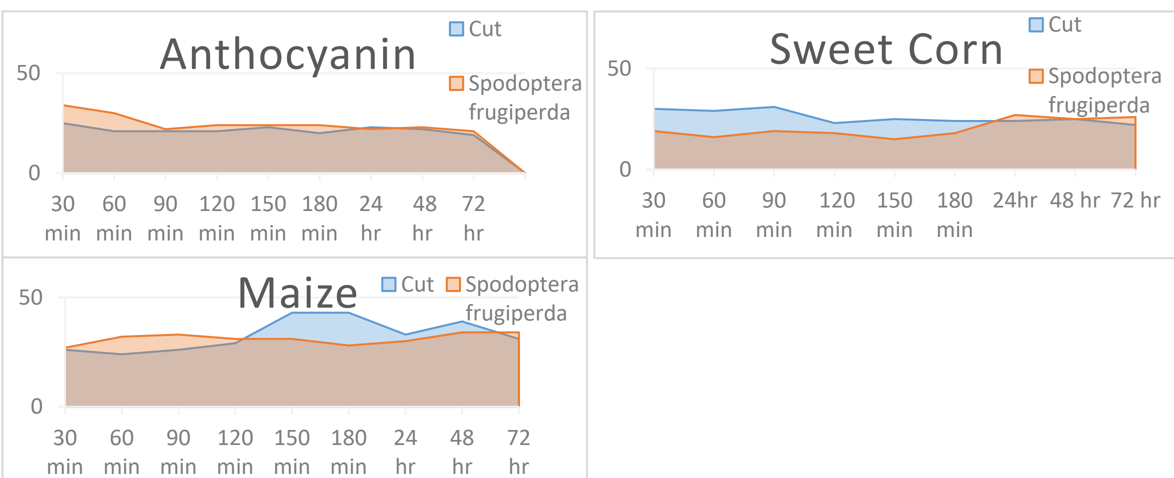

Figure 4. Temporal changes in VOC sensor responses of sweet corn, anthocyanin corn, and maize following mechanical cutting and *Spodoptera frugiperda* infestation over short-term (minutes) and long-term (hours) periods.

5.3 Plant Status Classification Using Artificial Intelligence Analysis

Plant status classification based on VOCs signals was evaluated using multiple artificial intelligence algorithms to compare quantitative performance, result stability, and practical applicability. The main findings are summarized as follows.

1. Structural separation using Linear Discriminant Analysis (LDA)

LDA demonstrated that VOC signals from healthy plants, insect-infested plants, and mechanically damaged plants could be structurally separated. This observation is consistent with the PCA results presented in the previous section, confirming that each plant condition exhibits distinct VOC emission patterns. However, for quantitative classification, LDA achieved an accuracy of approximately 75% with an F1-score of 0.75, indicating the limitations of linear models when feature overlap occurs.

2. Unsupervised grouping using K-means clustering
K-means clustering was applied to explore the intrinsic structure of the VOC data without using class labels. The results showed a partial tendency for clustering according to plant status. Nevertheless, significant overlap between insect-damaged and mechanically damaged samples reduced classification reliability. The method achieved an accuracy of 59.3% and an F1-score of 0.59, suggesting that it is more suitable for exploratory analysis rather than real-time warning applications.

3. Performance of Linear Support Vector Machine (Linear SVM)
Among the evaluated methods, the Linear SVM demonstrated the highest classification performance. The resulting decision boundaries effectively distinguished healthy plants from insect-infested and mechanically damaged plants, indicating superior robustness compared with other linear approaches. In quantitative terms, Linear SVM achieved an accuracy of approximately 93.52% and an F1-score of around 0.93, reflecting a good balance between precision and recall. This balance is particularly important for the early detection of insect infestation. Furthermore, the classification results remained consistent across multiple maize varieties, demonstrating the model's ability to generalize despite genetic differences among plants.

Considering quantitative performance metrics (accuracy and F1-score), stability across maize varieties, the risk of overfitting, and practical constraints, the Linear SVM was selected as the core classification model. Linear SVM provides a suitable balance between accuracy, robustness, and computational efficiency, making it well suited for real-time monitoring and early warning of fall armyworm infestation in maize crops (Figure 5).

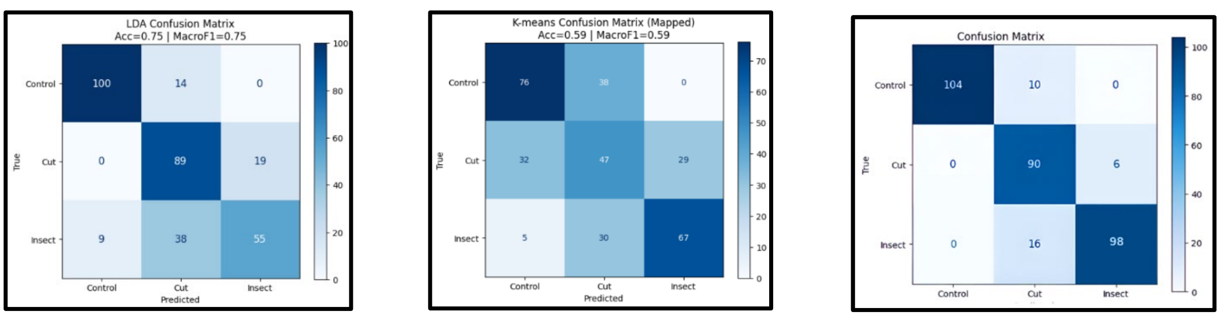

Figure 5. Confusion matrices comparing the classification performance of Linear Discriminant Analysis (LDA), K-means clustering, and Linear SVM for maize plant status classification based on VOC signals.

6. Conclusion

This study demonstrates that e-nose combined with artificial intelligence can effectively detect and classify maize plant status based on VOCs signals. The system clearly differentiated healthy plants, plants infested by the fall armyworm (*Spodoptera frugiperda*), and plants subjected to mechanical damage. PCA confirmed a well-defined data structure, with the first two principal components explaining 98.901% of the total variance. Temporal analysis showed that insect infestation induced sustained VOC emissions, whereas mechanical damage resulted in short-term responses. For plant status classification, Linear SVM achieved the most suitable performance, with an accuracy of approximately 93.52% and an F1-score of around 0.93, while maintaining stable results across different maize varieties. Considering both classification performance and computational efficiency, Linear SVM was selected as the core model for the system. Overall, the proposed framework provides a reliable basis for real-time detection and monitoring of fall armyworm infestation in maize.

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Biographies

Pinyada Kaewket is a 17-year-old Grade 11 student in the Gifted Computer Program at Prince Royal's College. She is passionate about engineering and biotechnology. Her remarkable achievements include winning first place at the national level for the GreenWaste project at the Young Electronics Innovators 2021 and the Thailand ICT Awards 2022, along with receiving the Asia-Pacific ICT Alliance Award. In 2026, She earned a Gold Medal at the Young

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Purimphat Sangkeaw, a 17-year-old Grade 11 student in the Gifted Computer Program at Prince Royal's College, has a strong interest in engineering and biotechnology. He has experience in coding and system development, participating in FIRST Tech Challenge Thailand 2025, and won a Gold Medal at the Young Scientist Competition 2026 (North Region). Additionally, he co-received research funding from the Agricultural Research Development Agency (ARDA) and plans to pursue higher education in Computer Engineering and Biomedical Engineering.

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