The Use of MQx-based System for Characterization and Optimization of Plant-derived Volatile Organic Compounds

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***Abstract*— The agricultural sector faces escalating challenges from pest issues exacerbated by climate change, which alters the distribution and behavior of insect pests, threatening crop yields and food security globally. While traditional chemical pest control methods exist, there is increasing interest in sustainable alternatives, such as plant-derived Volatile Organic Compounds (VOCs), which show potential for environmentally friendly pest management. Certain plants, including rosemary, peppermint, and lavender, emit VOCs capable of repelling pests, aligning with principles of integrated pest management and climate-smart agriculture. Advances in sensor technology now allow precise detection and analysis of these plant-produced VOCs, facilitating research into their composition, concentration, and effectiveness for pest control. Additionally, understanding the dispersal range of VOCs is essential to optimize the placement of aromatic plants in agricultural systems for maximum pest deterrence. This study aims to characterize the gases emitted by rosemary, peppermint, and lavender using various gas sensors, and additionally, to determine the maximum detection range of these emissions to enhance pest control strategies. For data classification, Machine Learning (ML) techniques were employed to enhance the system's performance. With all features, Boosted Trees achieved 77.66% accuracy, while reducing to 5 features improved accuracy to 80.4%. The model effectively distinguishes temperature patterns between distances, though the confusion matrix shows minor misclassifications, suggesting potential for refinement.**

Keywords- pests; aromatic plants; sustainable agriculture; gas sensors; pest repellent.

I. INTRODUCTION

The agricultural sector faces significant challenges due to pest problems, which can severely impact crop yields and food security. As climate change continues to alter ecosystems, the geographic distribution and behavior of agricultural insect pests are shifting, creating new threats for farmers worldwide [1]. To address these evolving challenges, various pest control methods have been developed and implemented, ranging from traditional chemical approaches to more sustainable and ecological management strategies [2].

In recent years, there has been a growing interest in alternative pest control methods that are both effective and environmentally friendly. Among these, the use of plant-derived Volatile Organic Compounds (VOCs) has gained attention as a potential tool for pest management [3]. Plants such as rosemary, peppermint, and lavender are known to produce a variety of gases that can repel or deter insect pests [4]. These natural compounds offer a promising avenue for sustainable pest control, aligning with the principles of integrated pest management and climate-smart agriculture [2].

Advancements in sensor technology have enabled researchers to detect and analyze these plant-produced gases with increasing precision [5]. These sensors can provide valuable data on the types and concentrations of VOCs emitted by plants, offering insights into their potential effectiveness pest control applications [6]. Understanding the composition and concentration of these plant-derived gases is crucial for developing effective pest management strategies based on their repellent or insecticidal properties [7], [8].

The distance that plant-produced gases can reach is an important factor in determining their efficacy for pest control. While the dispersal of VOCs depends on various environmental factors, such as wind speed and temperature, recent studies have begun to investigate the spatial dynamics of these compounds in agricultural settings [9]. This knowledge is essential for optimizing the placement of aromatic plants or their extracts in crop systems to maximize their pest control potential [10], [11].

The aim of the study is to characterize the gases emitted by specific plants (Rosemary, Peppermint, and Lavender) to prevent pest presence, by using different types of gas sensors. Additionally, the study seeks to determine the maximum detection range of these emissions.

The rest of the study is divided into seven sections. Section II details the most relevant reported studies, whereas Sections III and IV describe the proposal and test bench. The Results are explained in Section V, and in Section VI, a

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discussion is presented. Finally, conclusion and future perspective are shown in Section VII.

II. RELATED WORK

This section summarizes the current findings in gas characterization, sensor monitoring and usage, and pest management.

Recent studies on gas detection and analysis in plants by using sensor technologies have gained significant attention in agriculture, environmental monitoring, and plant health assessment. Several studies have explored the use of various sensor types and systems for this purpose. In 2024, Díaz Blasco et al. [12] investigated the use of Metal-Oxide (MQ) sensors which are sensible to different gases. These gas sensors were used for classifying essential oils from *Cistus ladanifer* plants. Their work demonstrated the feasibility of using low-cost gas sensors to differentiate between essential oil samples based on their VOC profiles. This approach shows promise for rapid and in-situ analysis of plant-derived gases. In a related study in the same year, Ahmad et al. [13] developed a LoRaWAN-based network for estimating harvest time in *Cistus ladanifer* crops. While not directly measuring plant gases, this work highlights the potential of integrating sensor networks with long-range wireless communication technologies for agricultural applications.

The importance of monitoring plant gases extends to pest management in sustainable agriculture. Bouri et al. [14] reviewed climate-smart pest management techniques, emphasizing the role of precision agriculture tools, including sensors, in monitoring and managing pests. Similarly, Kanwal et al. [4] discussed the integration of precision agriculture techniques for pest management, highlighting the use of sensors for pest monitoring and detection. Additionally, El-Zaeddi et al. [15] characterized the volatile composition of essential oils from aromatic herbs grown in Mediterranean regions. Their work provides valuable insights into the diverse range of volatile compounds produced by plants, which can inform the development of targeted sensing technologies.

On another note, in 2023, Alabi et al. [16] studied the effects of essential oil blends on rumen fermentation and greenhouse gas emissions in livestock. While focused on animal agriculture, this work underscores the importance of analyzing plant-derived compounds and their impact on gas production in biological systems.

In conclusion, numerous papers and experiments are similar to the research currently in progress. The objective, in comparison to related work, is to collect all the benefits provided by these studies, merging them with the concept of pest detection and plant damage prevention, and incorporating them into our system.

Nevertheless, there are a series of open issues that should be solved, especially the ones related to the cost of electronic devices to be installed in the crops. Additionally, the possibility of developing unassisted sensors is crucial for decreasing, among others, the cost of production of final products (e.g. reducing the amount of fuel required for farmers' displacements). Finally, it is so important to determine the number of devices required for covering a crop to be sure that measurements are significative enough. For this reason, in this paper, we have created a device capable of identifying different profiles of aromatic plants. Additionally, the presence of plants is measured at different distances to know the ratio of action of only one plant. As we already commented, the use of this type of plants mixed with other crops helps farmers to reduce or even eliminate the use of chemical pesticides in crops, protecting then, the environmental from unnecessary pollutants.

III. PROPOSAL

This study aims to develop a low-cost system for identifying aromatic plants using MQ family sensors integrated into a gas monitoring node [12]. In the market, it is possible to find a vast variety of gas sensors with different manufacturing techniques. Most of them require some kind of maintenance [17][18]. However, MQx sensors do not require it [19].

A. *Introduction to MQ Sensors*

MQ sensors, based on metal oxides, are known for their high sensitivity and rapid response times, making them suitable for applications such as flammable gas detection, air quality assessment, and the identification of compounds in breath. Each MQ sensor model is designed to detect specific chemical components in the air, offering flexibility across various monitoring applications.

B. *Selection of Sensors and Cost Efficiency*

Seven MQ sensors were selected due to their accessibility and low cost, generally priced between 1.5 to 2 € per sensor. This affordability makes MQ sensors a practical choice for many experimental and environmental monitoring applications. These sensors were selected based on a previous study conducted by Viciano-Tudela et al. [20].

C. *MQ Sensor Structure and Functionality*

Each MQ sensor contains an electrochemical sensor that changes its resistance upon exposure to certain gases. This resistance change enables the measurement of gas concentrations in the environment. Each sensor includes a heating element, which raises the temperature of a metal wire, typically composed of tin dioxide (SnO_2), to enhance sensitivity to gas. For safe operation, sensors are enclosed in a double-layer stainless steel mesh, preventing the heating element from affecting surrounding materials. The sensor's internal circuits comprise a heating circuit and a measurement circuit, which detect resistive changes indicative of gas concentration.

D. *Additional Environmental Monitoring with DHT11 Sensor*

A DHT11 sensor was incorporated to monitor temperature and humidity, as these variables can influence the accuracy of gas sensor readings. The DHT11 sensor measures temperature with an accuracy of ±2 °C within a 0 °C to 50 °C range, and humidity with ±5% accuracy within a 20% to 90% range. The sensor operates at a sampling rate of 1 Hz, enabling continuous environmental monitoring.

E. *System Processing and Data Management*

The MQ sensors and the DHT11 sensor are managed via an Arduino Mega 2560 microcontroller board, chosen for its high number of analog inputs, essential for processing data from multiple sensors. The board's ATmega2560 processor features 54 digital I/O pins (15 with PWM output capability), 16 analog inputs, and 4 UARTs for serial communication. This microcontroller acts as the system's central processing unit, collecting data from the sensors, processing it, and storing it in a database, as can be seen in Figure 1.

F. *Data Storage and Real-Time Monitoring*

The prototype system includes data storage in a MySQL database, allowing for real-time review of measurements. Additionally, a real-time clock is integrated to timestamp each measurement, facilitating data analysis.

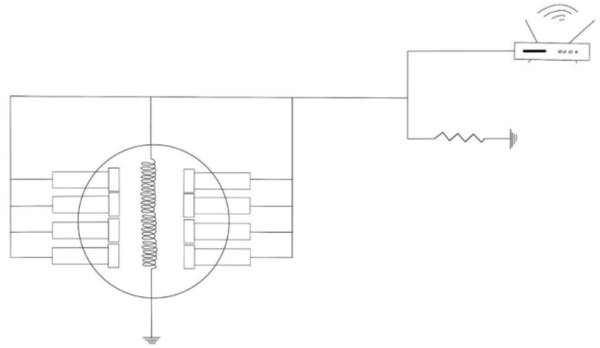

Figure 1. Illustration of the proposed sensor node consisting of 7 MQ gas detector connected to the router.

G. *Application for Aromatic Plant Identification*

This setup enables precise monitoring of aromatic plants by leveraging the sensitivity and versatility of MQ sensors to detect the unique chemical components emitted by these plants. By analyzing data from the sensors, the system can identify and differentiate specific aromatic plants efficiently and economically.

IV. TEST BENCH

This study uses gas sensors to identify three aromatic plants from the Lamiaceae family: rosemary, lavender, and mint. Emissions from each plant were measured at different distances and times to analyze their effectiveness as pest repellents. Statistical analysis will help differentiate the species and optimize sensor use in aromatic plant monitoring.

A. *Plant description*

For our tests, three varieties of aromatic plants commonly found in different crops were selected, all belonging to the Lamiaceae family. The first is rosemary (*Salvia rosmarinus*), a woody perennial plant with green leaves and purple flowers. Lavender (*Lavandula angustifolia*) in Figure 2, a perennial plant with lanceolate leaves and purple flowers, was also used. Finally, specimens of mint (Mentha) were included, which are herbaceous perennials with green leaves and white or purple flowers, although, at the time of the measurements, the mint plants did not have flowers.

A) **B)**

Figure 2. Plant Sample. A. Corresponds to Lavandula angustifolia. B. Corresponds to mint.

B. *Data Gathering Methodology*

To characterize each plant, the procedure followed is explained as follows. First, the sample plant (*Salvia rosmarinus*, *Lavandula angustifolia*, or mint) was placed inside the measurement device. The sensors were turned on, and, after 24 hours, the data collection process was stopped. Once the data collected was stored, sensors were turned off.

This procedure was meticulously repeated for each plant species in the experiment, and a total of three trials per species were conducted. The measurement device was positioned with exact precision at one centimeter from the plant like in Figure 3. After completing all measurements at this distance, the device was then placed ten centimeters, and finally thirty centimeters from the plant. Throughout, the above process was consistently followed to obtain the required data for each plant species.

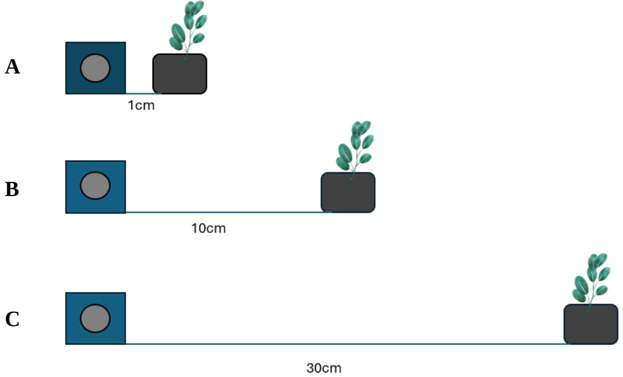

Figure 3. Assembly of the experiment at different distances. A. 0 cm separation from the plant; B. 10 cm separation from the plant; C. 30 cm separation from the plant.

It is important to note that the data collected during the first hour of each trial should be excluded, as this is the estimated warm-up period required for the gas sensors to reach optimal performance.

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C. Data Analysis Procedure

For the data analysis, the first step is to compare the variation in readings based on the type of aromatic plant analyzed and the distance at which gas sensors are positioned at different times of the day. This approach aims to determine whether the plants maintain consistent effectiveness over time or if there are specific periods during the day when their pest-repelling capabilities are more robust. Suppose fluctuations in data are observed at the start of measurement that later stabilize. In that case, it will be considered that the sensor requires an initial warm-up period, which may affect the readings. For this reason, a prolonged measurement period is used for each plant to determine the sensor's stabilization time.

To evaluate each plant's effective range, the sensors are placed at controlled, progressively increased distances, observing any changes in readings. A reduction in values as distance increases could indicate that the plant has reached its maximum effective range in repelling pests.

TABLE I. SUMMARY OF THE ACHIEVED ACCURACY IN CONDUCTED TESTS

Nº of features	**Model**	**Accuracy Training-Validation (%)**	**Test (%)**
38/39 (all)	Boosted Trees	88.87	77.66
9/39 (all)	Ensemble	97.95	72.21
5/39 (all)	SVM	98.23	80.43

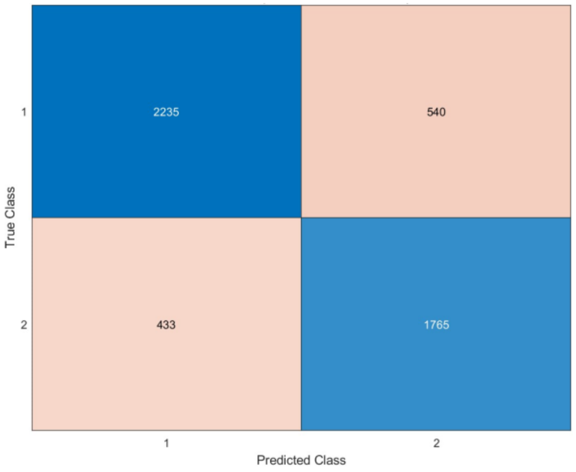

Figure 4. Confusion matrix of selected ML-based classification model.

Once the minimum required measurement time is established, the next critical step is to ensure precise differentiation between the three plant varieties used in the experiment. This differentiation is achieved through the inclusion of controls and statistical methods. The goal is to identify which, or if a combination of sensors, can accurately determine the type of plant present and the effective range of its action. The sensors that have demonstrated the highest accuracy for these parameters will be selected to optimize precision in future measurements and analyses.

V. RESULTS

In this section, we will present the collected data and the results produced by the classification models. The data analysis includes a statistical overview of the collected data. Additionally, the classification outcomes are assessed using established metrics and represent the models that will be included in the node.

A. Data processing and classification

For data classification, the generated dataset is divided into two datasets. Raw values from the data obtained from plants closest and 10 cm to the sensors are used to train the model, and data from 30 cm apart from the sensor is used to test the generated models. The metric selected to test these models is accuracy.

In Table 1, when all features are included, an accuracy of 77.66% is achieved with Boosted Trees. On the other hand, in order to reduce the number of features, up to 9 features, it is possible to reach a 72.21% accuracy, reducing its precision. Nevertheless, when reducing to 5 features, it is possible to achieve the highest accuracy. The classification model achieved an accuracy of 80.4% in distinguishing between temperature measurements taken from plants by a sensor positioned at 0 cm and 10 cm from the plants compared to a sensor placed at 30 cm. This accuracy metric indicates the model's ability to correctly classify the temperature data based on sensor distance. Specifically, an accuracy of 80.4% means that, on average, the model correctly identified the temperature measurement source in 80.4% of the test cases. This suggests a reasonably effective differentiation between the temperature profiles captured at these three distances, though some overlap in temperature readings between the two distances may still exist. The confusion matrix can be seen in Figure 4.

The matrix provides detailed insights into the model's classification performance. The rows represent the actual(true) classes, with "1" and "2" corresponding to temperatures (26ºC and 27 ºC) at 0 and 10 cm compared to 30 cm. The columns represent the predicted classes. In this case, of the samples belonging to Class 1, the model correctly identified 2,235 instances, while misclassifying 540 instances as Class 2. For Class 2, the model accurately classified 1,765 instances and misclassified 433 instances as Class 1. The matrix reveals a balanced distribution of correct classifications for both classes, with high true positive and true negative counts indicating the model effectively distinguishes temperature patterns. However, some misclassifications suggest potential for further refinement, showing the model's strong generalization across sensor depths tested.

VI. DISCUSION

The results of this study demonstrate the potential of using low-cost MQ sensors to detect and analyze the VOCs emitted by aromatic plants such as rosemary, lavender, and peppermint for pest control applications. These findings align with recent research on plant-derived VOCs, supporting their viability as eco-friendly alternatives to synthetic pesticides. By leveraging the sensitivity of MQ sensors, we could identify the unique VOC profiles of each plant, providing insight into their repellent properties and practical ranges.

A. Effectiveness of MQ Sensors for VOC Detection

The MQ sensors displayed sufficient sensitivity to detect characteristic VOCs of the studied plants at varying distances, showing promise as a tool for aromatic plant identification. Given the low cost and wide availability of MQ sensors, they present a practical solution for integrating VOC detection into pest management practices, particularly in regions or settings where advanced instrumentation is economically or logistically unfeasible. This study's findings are consistent with work by Díaz Blasco et al. [12] and Ahmad et al. [13], which demonstrated the practicality of MQ sensors in agricultural applications, including crop classification and essential oil analyses remains in enhancing the accuracy and specificity of these sensors. For instance, while the sensors successfully differentiated VOC profiles at proximity (0-10 cm), accuracy diminished slightly at greater distances (30 cm), indicating potential limits in the sensors' effective detection range. This decline in sensitivity may be due to environmental interference or the natural dispersion of VOCs over distance. Thus, further refinement in sensor placement and calibration could improve detection accuracy.

B. Implications for Sustainable Pest Management

This study highlights the potential role of VOCs from aromatic plants in Integrated Pest Management (IPM) strategies, contributing to climate-smart agriculture by reducing the reliance on synthetic pesticides. By characterizing the VOC emission patterns of rosemary, peppermint, and lavender, we can inform farmers on the optimal placement and quantity of these plants within crop fields to enhance their pest-repelling effectiveness. These findings are aligned with the work by El-Zaeddi et al. [15] on the role of Mediterranean herbs in pest management.

C. Environmental and Operational Considerations

Integrating the DHT11 sensor for monitoring temperature and humidity proved essential, as these environmental factors significantly influence gas sensor performance. Data showed that changes in humidity and temperature led to slight variations in the sensors' readings, a well-documented limitation in previous studies on MQ sensors' environmental sensitivity. This suggests that real-time monitoring is crucial to ensuring reliable and consistent data from MQ sensors, particularly in field settings where climate conditions fluctuate.

Future research should consider implementing calibration algorithms that adjust sensor readings in real time based on environmental conditions to address these challenges. Additionally, exploring alternative or supplementary sensor technologies, such as electrochemical or infrared sensors, may enhance the accuracy of VOC detection across a broader range of environmental conditions.

D. Data Analysis and Model Optimization

The machine learning models applied in this study achieved an accuracy of up to 80.4% in distinguishing between aromatic plants based on sensor data, validating the potential of data-driven approaches for plant identification. Notably, the accuracy was highest when using a reduced set of five features, suggesting that sensor data can be streamlined without compromising classification performance. This supports the hypothesis that certain VOC compounds indicate specific plant types and that focusing on these compounds can improve model efficiency.

Nonetheless, the moderate misclassification rate observed in the confusion matrix indicates potential for optimization. Future work could involve experimenting with different machine learning algorithms, such as deep learning models, to enhance classification performance. Additionally, increasing the number of sensor types in the node could provide a more comprehensive VOC profile, potentially improving accuracy further.

E. Limitations and Future Directions

While the findings demonstrate the feasibility of using MQ sensors for plant VOC identification, limitations remain. MQ sensors, while cost-effective, lack the specificity of advanced Gas Chromatography-Mass Spectrometry (GC-MS) used in laboratory settings. This limitation could be addressed by combining MQ sensors with more selective technologies in a hybrid sensing system, providing broader coverage of VOCs with improved accuracy.

Future studies should also investigate the temporal dynamics of VOC emissions throughout the day to understand how plant VOC release patterns vary under different environmental conditions. By establishing these patterns, the effectiveness of VOCs as pest deterrents can be optimized based on real-time environmental monitoring. Furthermore, long-term field trials are recommended to validate these findings under real-world agricultural conditions, as laboratory settings cannot entirely replicate the complexities of open-field environments.

VII. CONCLUSION AND FUTURE WORK

Based on the results obtained, it has been demonstrated that the MQ sensor effectively detects VOCs emitted by aromatic plants. The data collected enables each plant to be characterized using artificial intelligence algorithms, achieving a significant level of accuracy in species identification and distance measurement.

Nevertheless, it is necessary to expand the dataset and conduct further measurements under varying environmental conditions to enhance the precision and consistency of plant characterization. This would allow the models to be fine-tuned and their robustness increased in field scenarios. Additionally, incorporating new variables, such as temporal variations in VOC emissions, could help identify optimal periods for pest control effectiveness.

For future work, once an accurate characterization of the aromatic plants is achieved, estimates of the adequate spatial coverage of each species could be made. This will allow for applying these findings to commercial-scale crops, optimizing the placement of plants in agricultural systems to maximize their repellent effect and contribute to a more sustainable integrated pest management approach.

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