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Odors Detection and Recognition Based on Intelligent E-Nose



Abstract: - Electronic noses have become more common as a result of developments in sensor technology, machine learning (ML), and Artificial Intelligence (AI). At the moment, the majority of e-nose research is conducted in laboratories; access from other locations is not possible with e-nose. Very few real-time smell detection applications, including tiny drones equipped with commercial gas sensors or biosensors made of insect antennas, have been created. The scope of this work is to design an intelligent E-Nose for odors detection. Smell Inspector developer kit has been used to get measurements. The Smell Inspector consists of sensors for temperature and humidity in addition to four smell iX16 chips. The Smell Inspector creates digital fragrance fingerprints using a variety of separate gas detectors. The approach for object recognition and classification using artificial intelligence techniques is presented in this paper. These techniques include Machine Learning (ML), clustering, and regression algorithms. Using the K-Nearest Neighbor (KNN) algorithm, the experimental results' array sensors were able to recognize; clean air, onion, garlic, coffee, spices, lemon, vinegar, gasoline, petrol, diesel, and perfumes with 78% accuracy rate.

Keywords: E-Nose, Array Sensors, Smell Recognition, Artificial Intelligence, Feature Extraction, PCA Machine Learning, KNN, Classification, Noise Reduction.

I. INTRODUCTION

Like a human nose, an electronic device called an e-nose may be able to identify and detect various gases and scents. The E-Nose can distinguish between various scents and is not susceptible to fatigue or the illness, while not having the same level of sensitivity as a human nose. The majority of current E-Noses are made for standalone or lab-based uses. In order to view the sample prediction results, the user needs to be at the location of the E-Nose. Internet of Things (IoT) development is progressing quickly. IoT technology has proven beneficial in a number of industries, including manufacturing, transportation, health, logistics, and agriculture. IoT generally allows for the automation of several smart devices, technologies, and applications by connecting them. E-nose creates a distinct fragrance pattern by utilizing a non-specific chemical sensor array. The array's many sensors result in a greater processing load, more data that needs to be transferred, higher energy consumption, and possibly worse machine learning performance. Smell Inspector developer kit, Low and high quality MQ family sensors or sensors like silicon CMOS type sensor, and C 5-QCM sensor module from AROMA Bit Company can be used in an E-Nose.

The development of electronic olfaction has provided a transformative opportunity to augment the human sensory capabilities. In the fields of viticulture and culinary arts, the "e-nose" exhibits an extraordinary ability to identify nuanced aromas and flavors that elude the capabilities of humans. Through the use of electronic olfaction, the precision of various quality control procedures, such as flavor profiling and spoilage detection, has been greatly enhanced. This technology has allowed the industry to redefine the way we consume food. This paradigm shift opens up a world of possibilities where the gustatory and olfactory senses work harmoniously. Examples of E-Nose applications include human robots with a sense of smell, food quality monitoring, gas leak detection, explosives detection, and drug detection. Figure 1 shows the intelligent E-Nose concept.

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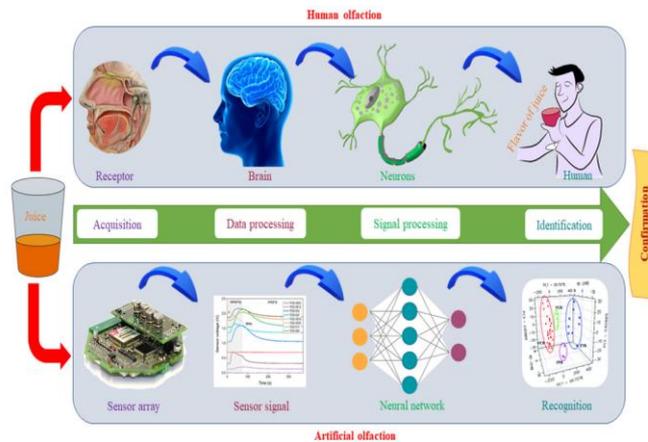


Figure 1: Intelligent E-Nose Concept [25].

The rapid emergence and evolution of electronic olfaction has also opened up the possibility of developing sensor networks that can be used to identify and monitor the various types of pollutants and toxic gases in the environment. This technology could help prevent harmful effects from happening in the first place. As the world struggles with an increasing ecological crisis, the “*e-nose*” could become a vital part of the solution by providing timely and accurate information.

The integration of electronic olfaction and environmental monitoring can create a comprehensive and proactive approach to preserving the environment. It brings together the domains of conservation and technology in an unprecedented way.[1].

The integration of electronic olfactory systems into various industries is linked to the resonance of Deep Learning (DL), AI, and ML. The cognitive architectures that are built on top of these technologies can provide a symphony of sensory perception that surpasses the limitations of traditional paradigms.[2]-[3]. AI is capable of producing an “*e-nose*” that is endowed with context-awareness and adaptability, similar to that of its biological sibling. Through the use of ML and pattern recognition techniques, the systems can identify and interpret complex odor details. DL, on the other hand, has the capability to navigate through the maze of odor codes and find hidden ones. The journey into AI, ML, and DL places the “*e-nose*” in a cognitive category that surpasses its biological counterpart.[4]-[5].

The intersection of these diverse domains has created a fertile ground for multidisciplinary discourse. The “*e-nose*” is a dynamic synthesis of scientific knowledge that brings together the disciplines of engineering, biology, chemistry, and data science. This is a framework for bringing together the multiple strands of scientific knowledge that are related to the field of electronic olfaction. As they collaborate to create an avant-garde trajectory, the researchers will be able to interact with the diverse dialects of the community. The interactions between different disciplines within the “*e-nose*” create a dynamic crucible that encourages innovation. These challenges manifest into new directions and unleash the potential of unexplored regions.[6]-[7].

The concept of the “*e-nose*” is an embodiment of a future that departs from current conceptualization. Its development is characterized by the simultaneous realization of a miniaturized and portable device that can be easily carried around, as well as the ethical implications of protecting the privacy of our data. Due to the complexity of the “*e-nose*” development, the ethical quandaries surrounding its use and distribution are becoming increasingly prominent. This is why it is important that the regulatory environment is designed to accommodate the needs of both the research and industry sectors. As the technological and scientific communities explore its applications, they are poised to seize the opportunity to create new collaborative ventures[8].

Despite their many advantages, electronic noses also have some limitations. One of the main challenges is achieving a high level of selectivity, or the ability to distinguish between different odorants. Some E-Noses may also be prone to sensor drift or interference from other smells, which can lead to false readings. Additionally, E-Noses may require regular calibration and maintenance to ensure accurate results.

In reminder of sections, the study and survey on modern E-Nose and smell detection systems are presented in section II. Section III presents our work approaches. The current results are presented in Section IV. We will finally talk about the conclusion and upcoming projects in section V.

II. LITERATURE REVIEW

We review recent frameworks and applications of sensor array-based electronic noses in this section.

Studies have demonstrated the potential of E-Nose sensor array innovation in a variety of industries, including the food and beverage, medical diagnostic, monitoring, security, and defense sectors. Array sensors have been used in the food industry to identify food flavor and smell, detect food deterioration and tainting, and verify food quality. E-noses have been used in medical diagnosis to identify conditions such as diabetes, lung cancer, and urinary tract infections. E-Noses have been used in natural monitoring to identify dangerous synthetic chemicals and air pollution. E-Nose sensors have been used in security and defense to detect bombs and identify dangerous synthetic materials.

This literature review aims to give a thorough overview of the state of the area of electronic olfaction as it is right now. It examines many studies that address the conception, application, and use of electronic noses. The literature study provides a thorough examination of the state of electronic smell, along with an assessment of its opportunities and drawbacks. It also draws attention to the nexus between advanced technology and the senses of humans.

Willeford[9] investigates the intriguing concept of the Luminescence Hypothesis of Olfaction. This hypothesis suggests that the perception of odors could be attributed to the luminescence properties of odor molecules. While traditional olfactory theories focus on odorant-receptor interactions, the Luminescence Hypothesis proposes an alternative mechanism. The study explores the connection between luminescence and odor perception, potentially challenging existing models. This novel perspective adds to the ongoing discourse in the field of olfaction, shedding light on new avenues of research and understanding.

ditama et al.[10]concentrated on electronic nose sensor development using artificial neural network backpropagation for Lombok agarwood classification. Their research aimed to accurately classify different types of agarwood based on unique aroma profiles. This study demonstrated the potential of artificial neural networks in enhancing the authenticity and quality control of valuable natural products.

Phukkaphan et al.[11] employed a gas sensor array-based electronic nose for detecting milk spoilage. This research contributed to food safety by offering a rapid method to assess milk quality. By analyzing sensor responses and employing machine learning, the electronic nose accurately distinguished between fresh and spoiled milk.

Borowik et al.[12] developed a low-cost electronic nose for detecting pathogenic fungi in crops. The study emphasized the potential of combining sensor technology with classification algorithms for rapid and reliable agricultural diagnostics. The researchers successfully detected *Fusarium oxysporum* and *Rhizoctonia solani* using a reduced sensor array.

Tan et al.[13] provided a comprehensive review of the applications of electronic noses and tongues in determining food quality-related properties. The review encompassed various food types and sensor technologies, highlighting the diverse range of uses for electronic noses and tongues in the food industry.

Tatli et al.[14] addresses the impact of urea fertilizer on volatile organic compound (VOC) emissions from cucumber fruits. Utilizing a MOS (Metal Oxide Semiconductor) “*e-nose*” sensor array, the study demonstrates rapid and non-destructive detection of changes in VOC profiles due to urea application. The work contributes to precision agriculture by offering a tool for monitoring the effects of fertilization on plant health. The MOS “*e-nose*” sensor array proves to be a valuable asset in assessing the physiological responses of plants to various treatments.

Meléndez et al.[15] present a portable electronic nose designed for discriminating 2,4,6-Trichloroanisole (TCA), a compound responsible for cork taint in wines. The study integrates both digital and analog chemical sensors in the electronic nose setup. By employing a combination of sensor technologies and signal processing methods, the portable device achieves accurate and sensitive detection of TCA, a critical factor in quality control within the wine

industry. The research showcases the potential of electronic noses in addressing specific quality issues in various applications.

Tong et al.[16] concentrate on designing and optimizing an electronic nose sensor array for real-time and rapid detection of vehicle exhaust pollutants. The study acknowledges the urgent need for air quality monitoring, particularly in urban environments where vehicle emissions contribute to pollution. The researchers develop an electronic nose configuration capable of identifying and quantifying specific pollutants in vehicle exhaust. Through rigorous optimization and testing, the sensor array proves effective in providing quick and accurate data on air quality, aiding pollution control efforts.

Gancarz et al.[17] focuses on detecting and measuring aroma compounds during the wheat bread making process using an electronic nose. The study addresses the importance of aroma in food quality and consumer preference. The researchers introduce a novel method for analyzing signals from MOS (Metal Oxide Semiconductor) sensors in the electronic nose, enhancing the precision of aroma compound identification. The outcomes of this research contribute to the understanding of flavor development during food processing and highlight the potential of electronic noses in ensuring consistent product quality.

Shigaki et al.[18] design and experimental evaluation of an odor sensing method for a pocket-sized quadcopter. The research aims to leverage quadcopters for odor source localization and mapping. The innovative approach involves attaching an electronic nose to a small quadcopter, enabling it to detect and track odors in the environment. The study showcases the potential of such devices in various applications, including environmental monitoring, search and rescue missions, and agricultural surveillance.

John et al.[19] provide an overview of recent advances in chemi-resistive sensor-based electronic nose systems for food quality and environmental monitoring. The paper discusses the integration of chemi-resistive sensors in electronic noses, highlighting their role in detecting volatile compounds indicative of food quality and environmental conditions. The researchers investigate into the progress made in sensor technologies, data analysis methods, and applications. This comprehensive review informs readers about the state-of-the-art developments in electronic nose systems and their significance in ensuring product quality and environmental sustainability.

Ajiboye et al.[20] performs analytical determination of the load resistance value for MQ-series gas sensors, using MQ-6 as a case study. The study addresses the importance of optimizing sensor performance through the appropriate selection of load resistance values. By conducting experiments and analyses, the researchers provide insights into enhancing the sensitivity and accuracy of gas sensors, which are crucial for applications ranging from air quality monitoring to safety systems.

Simonenko et al.[21] present a comprehensive survey of literature on the emerging use of printing technologies in gas sensors. The study explores how printing techniques, such as inkjet and screen printing, are revolutionizing the fabrication of gas sensors. These approaches offer cost-effective and scalable methods for sensor production. The paper highlights the various materials, structures, and applications enabled by printing technologies, shedding light on their potential to shape the future of gas sensor development.

Julian et al.[22] introduces an intelligent mobile electronic nose system featuring a “hybrid polymer-functionalized quartz crystal microbalance” (QCM) sensor array. This research focuses on portable and real-time gas sensing applications. The hybrid sensor array incorporates both “polymer-based” and QCM-based sensors, enhancing sensitivity and selectivity. The study demonstrates the potential of the system in detecting volatile compounds, making it suitable for various scenarios, including environmental monitoring and food safety assurance.

Kaushal et al.[23] examines the applications of electronic noses combined with statistical and intelligent pattern recognition techniques for monitoring tea quality. The review underscores the significance of tea aroma in determining its quality and value. The researchers explore how electronic noses, in tandem with advanced data analysis methods, offer efficient tools for characterizing tea aroma profiles. The review consolidates current knowledge and insights, fostering a deeper understanding of electronic nose applications in the tea industry.

Arroyo et al.[24] present a wireless sensor network combined with cloud computing for air quality monitoring. The study addresses the challenges of collecting and processing air quality data in real time. By employing a wireless network of distributed sensors and cloud-based computing resources, the researchers establish a robust and scalable

solution for environmental monitoring. The paper discusses the benefits of this approach in terms of data accuracy, accessibility, and scalability, paving the way for enhanced air quality management strategies.

Roy et al.[25] focuses on the application of electronic noses for detecting food adulteration. The study recognizes the persistent issue of food fraud, where substances are added to deceive consumers and compromise product quality. The researchers discuss how electronic noses play a vital role in identifying adulterants by analyzing aroma profiles. The review assesses various methods and technologies employed in electronic nose systems, shedding light on their potential to combat food adulteration and uphold consumer trust.

Huang et al.[26] delve into the realm of machine learning-enabled graphene-based electronic olfaction sensors. The study emphasizes the significance of sensitive and accurate olfaction technology for various applications. By integrating graphene-based sensors with machine learning algorithms, the researchers enhance the capabilities of electronic noses. The paper not only presents the sensor technology but also assesses its olfactory performance through extensive experiments. The study contributes to the advancement of electronic nose systems, catering to diverse fields, including food, healthcare, and environmental monitoring.

Rasekh et al.[27] perform the analysis of the MAU-9 electronic-nose MOS sensor array components and artificial neural network (ANN) classification methods. The study centers on discriminating herb and fruit essential oils based on their distinct aroma profiles. By evaluating different sensor combinations and classification techniques, the researchers optimize the sensor array and ANN models to achieve accurate and reliable discrimination. This work contributes to the advancement of electronic nose systems for precise identification and quality control across various applications.

III. METHODOLOGY

The proposed E-Nose, system architecture, and the proposed AI model will be discussed in this section. Figure 2 indicates the proposed the high level of system architecture.

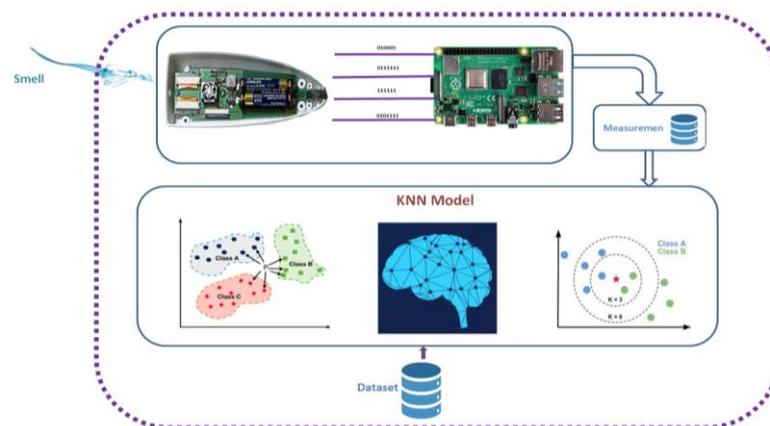


Figure 2: System Architecture.

Selecting the necessary hardware and tools is the first step of designing an E-Nose. In our case, we have been used a Raspberry Pi 3 model B microcontroller, Smell Inspector iX16 with 4 sensors each has 16 channels of measurement as an array sensors.

A- *Data Acquisition*

Four Smell iX16 chips, along with temperature and humidity sensors, are included in the Smell Inspector. The Smell Inspector creates digital fragrance fingerprints using a variety of separate gas detectors. Every 1.8 seconds, it captures a fresh digital fingerprint. Pattern recognition is the foundation for identifying smells. Every distinct smell and gas causes the sensor array to generate a different pattern of electric impulses. Temperature and humidity readings are included in the measurement, along with 64 channel resistance value cycles. A variety of feature channel types make up the 64 channels. Every feature channel has unique properties related to smell sensitivity. Every detector has sixteen channels. Different attributes are represented by each channel. Current detectors come with a variety of feature sets, including Type 1, Type 2, Type 3, and Type 4. Table 1 shows the types of feature sets in each detector.

Table 1: Types of Feature Sets in Each Detector.

| Detector Type | Ch1 | Ch2 | Ch3 | Ch4 | Ch5 | Ch6 | Ch7 | Ch8 | Ch9 | Ch10 | Ch11 | Ch12 | Ch13 | Ch14 | Ch15 | Ch16 |
|---------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|------|------|
| Type1 | 999 | 999 | 11 | 11 | 11 | 3 | 3 | 3 | 2 | 2 | 2 | 1 | 1 | 1 | 999 | 999 |
| Type2 | 999 | 999 | 999 | 999 | 999 | 9 | 9 | 9 | 6 | 6 | 6 | 5 | 5 | 5 | 999 | 999 |
| Type3 | 999 | 999 | 14 | 14 | 14 | 10 | 10 | 10 | 7 | 7 | 7 | 4 | 4 | 4 | 999 | 999 |
| Type4 | 999 | 999 | 15 | 15 | 15 | 13 | 13 | 13 | 12 | 12 | 12 | 8 | 8 | 8 | 999 | 999 |

There are totally 66 readings for all 64 channels (16 channels for each sensor) plus humidity and temperature. Only 44 channels readings were utilized, normalized, and standardized, to extract the features to train the machine learning model. Table 2 shows the list of total and utilized channels readings.

Table 2: List of Channels Readings.

| 66 Readings | 44 Readings |
|--|--|
| Ch1, Ch2, Ch3, Ch4, Ch5, Ch6, Ch7, Ch9, Ch10, Ch11, Ch12, Ch13, Ch14, Ch15, Ch16, Ch17, Ch18, Ch19, Ch20, Ch21, Ch22, Ch23, Ch24, Ch25, Ch26, Ch27, Ch28, Ch29, Ch30, Ch31, Ch32, Ch33, Ch34, Ch35, Ch36, Ch37, Ch38, Ch39, Ch40, Ch41, Ch42, Ch43, Ch44, Ch45, Ch46, Ch47, Ch48, Ch49, Ch50, Ch51, Ch52, Ch53, Ch54, Ch55, Ch56, Ch57, Ch58, Ch59, Ch60, Ch61, Ch62, Ch63, Ch64, Humidity, Temperature. | Ch1, Ch2, Ch3, Ch5, Ch6, Ch7, Ch9, Ch11, Ch12, Ch13, Ch14, Ch16, Ch18, Ch19, Ch21, Ch23, Ch24, Ch25, Ch26, Ch27, Ch28, Ch29, Ch30, Ch31, Ch33, Ch34, Ch35, Ch37, Ch38, Ch39, Ch41, Ch43, Ch46, Ch51, Ch52, Ch53, Ch54, Ch55, Ch56, Ch57, Ch58, Ch59, Ch60, Ch61. |

B- Feature Extraction

The raw data points on the concentration of volatile organic compounds (VOCs) from each sample collected during the data acquisition phase using the preplanned model. The ML model was trained with 15 features as a pre-classification step. When the features were reduced to 3, the ML model's presentation grew. To extract the features from the raw data in this case study, we use Principal Component Analysis (PCA) as in order to reduce dimensionality. Principal components analysis (PCA) is a technique that creates new, uncorrelated features from a dataset's original features.

The computation of eigenvectors and eigenvalues from the covariance matrix of the standardized data is a necessary step in the mathematical formulas for PCA. Below is a condensed summary of the steps that are involved:

Let X be the matrix that represents the standardized data, with a feature for each column and a data point for each row.

Compute the covariance matrix C of X .

$$C = \frac{1}{n-1} (X^T \cdot X) \quad (1)$$

Perform eigenvalue decomposition on C .

$$C = V \cdot D \cdot V^T \quad (2)$$

V is a matrix of eigenvectors, and D is a diagonal matrix of eigenvalues.

Depending on how much variance they explain or how many components are needed, the primary components are chosen.

The original data X is transformed into the new feature space X_{PCA} using the selected principal components.

$$X_{PCA} = X \cdot V_{\text{selected}} \quad (3)$$

C- Classification and Prediction

The classification algorithm k-Nearest Neighbors (KNN) utilized as a ML model. KNN is a lazy, non-parametric supervised learning technique that may be applied to regression and classification problems alike. Classifying a data point according to the majority class of its k nearest neighbors in the feature space is the main purpose of KNN. The general KNN steps are as follows:

Calculating Distance: Determine the separation between each point in the training set and the new data point. Depending on the issue, common distance measures include the Manhattan distance, the Euclidean distance, and others.

Choosing a Neighbor: Using the estimated distances, determines who the k-nearest neighbors are.

Voting in the majority: To classify a new data point, give it the class label that appears the most frequently among its k-nearest neighbors.

Regression (Selective): The average or weighted average of the target values of the k-nearest neighbors can be used as the projected value in regression tasks.

The following techniques are involved in utilizing KNN for classification in Python:

- **fit(X, y):** Fit the model with goal values (y) and training data (X).
- **predict(X):** Assume the given data to be the class labels.

Where X represents the input features and y is the target variable or class label

IV. RESULTS

The proposed work resultant as an intelligent E-Nose that could distinguish between various smells. Clean air, onion, garlic, coffee, spices, lemon, orange, vinegar, gasoline, petrol, diesel, and perfumes were the samples selected for this work. Different smells are produced by these kinds of samples. From totally 66 readings only 44 readings were utilized, standardized, and optimized to extract the features using PCA. Figures 3 and 4, show radar plot of measurements for all 66 features, and 44 selected features of the odors samples.

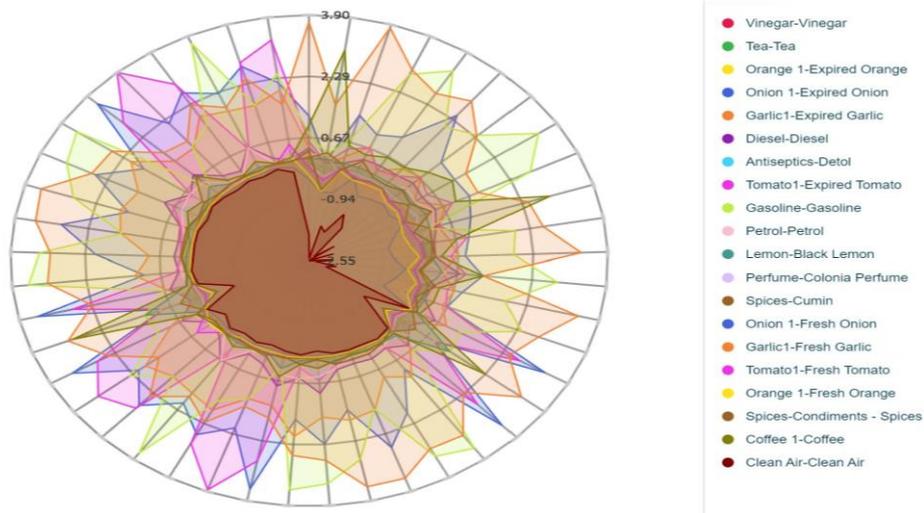


Figure 3: Radar Plot of All 66 Features and Data.

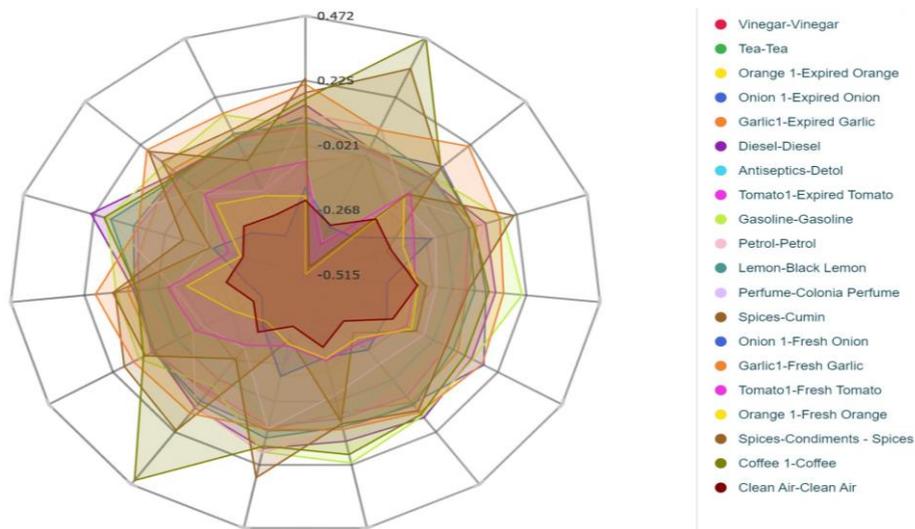


Figure 4: Radar Plot of 44 Features and data.

We collected 9,900 raw data points on the concentration of volatile organic compounds (VOCs) from each sample during the data acquisition phase using the preplanned model. The ML model was trained with 15 features as a pre-classification step. When the features were reduced to 3, the ML model's presentation grew. Table 3 shows the minimum and maximum value of each feature response for different odors.

Table 3: Min-Max Features Values of Different Samples.

| Samples | PC1 | | PC2 | | PC3 | |
|-----------|-------|------|------|------|------|-----|
| | Min | Max | Min | Max | Min | Max |
| Clean Air | -12.6 | 14.3 | -3.9 | 4.1 | -2.5 | 2.6 |
| Onion | -6.6 | 18.0 | -2.6 | 3.5 | -3.2 | 3.6 |
| Coffee | -7.8 | 9.8 | -4.5 | 12.2 | -2.8 | 3.9 |
| Garlic | -8.8 | 14.2 | -2.4 | 3.4 | -1.1 | 5.3 |
| Vinegar | -6.2 | 16.1 | 2.3 | 3.1 | -2.9 | 4.4 |
| Gasoline | -8.7 | 16.7 | -3.5 | 7.0 | -3.3 | 5.5 |

| | | | | | | |
|---------------|-------|------|------|-----|------|-----|
| Petrol | -11.6 | 15.5 | -2.8 | 4.5 | -3.0 | 4.3 |
| Diesel | -10.2 | 16.5 | -3.1 | 4.9 | -3.6 | 5.1 |
| Orange | -11.1 | 15.8 | -2.5 | 4.7 | -1.9 | 3.6 |
| Lemon | -13.4 | 11.6 | -2.1 | 4.4 | -2.7 | 4.2 |
| Spices | -16.5 | 17.3 | -3.5 | 5.5 | -2.1 | 2.6 |

Table 4 shows the accuracy of the suggested work when the ML model is applied with both raw and reduced features.

Table 4: Accuracy Comparison of Raw and Reduced Features.

| Algorithm | Accuracy | |
|------------|-------------|------------|
| | 15 Features | 3 Features |
| KNN | 67 % | 78% |

Figure 5 shows the designed system in the real environment.

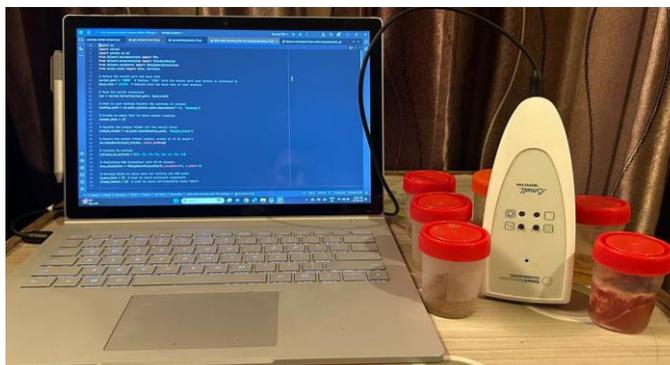


Figure 5: The Final Designed System.

V. CONCLUSION AND FUTURE WORK

This paper proposes an intelligent E-Nose based on Smell Inspector sensor array that can be used in future as a smell detection and recognition system. The centralization of VOCs serves as the input data for the ML (KNN) model. Every sample's real-time sensor readings are used to construct the usable dataset. 67% percent accuracy is shown by the KNN model that proposed and programmed in Python at an earlier stage of this work using 15 features from various sensor readings. Using 3 features from four separate sensors, the KNN algorithm produces an accuracy of 78%. The designed E-Nose can detect and recognize different scents (clean air, onion, garlic, coffee, lemon, gasoline, petrol, and diesel). This work is a part of Ph.D. research on intelligent E-Nose for odors detection and recognition. The core of this work is how to design our own classification model to classify multi-varieties. In future, the system will be integrated to function as a mobile robot that takes the results and transmits them via one of the modern communications technologies over long ranges. The final system will be as an intelligent mobile E-Nose for real time smell detection and recognition based on array sensor.

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