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DESIGNING AN E-NOSE PROTOTYPE BASED ON GAS SENSORS ARRAY

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***Abstract*- Nowadays, electronic olfaction or Electronic Noses (E-Noses) are mostly designed and developed for lab-based applications. In real-life scenarios, smell detection represents the external and internal responses to human being events. In Human Computer Interaction (HCI), detecting odorant molecules in the air plays a very important role in different conditions such as food quality, environmental monitoring, and security. Few real-time applications based on E-Nose have been developed, such as biosensors based on insect antenna or small drones with low-cost gas sensors. Smell detection and recognition as an environmental monitoring application using sensor array measurements represent the scope of this work. To increase the accuracy and application range of detection, six of high and low-quality sensors have been used to get measurements. In this study, the proposed E-Nose prototype consists of DF-NH3, MQ-136, MQ-135, MQ-8, MQ-4, and MQ-2 sensors. This work presents the methodology in terms of artificial intelligence techniques used for classification and object detection such as machine learning classification, clustering and regression algorithms. Using the K-Nearest Neighbors (KNN) algorithm, these sensors used in the experimental results were able to predict petrol, gasoline, perfumes, and others with a 71.1% accuracy rate.**

keywords: **E-Nose, Smell detection, Food quality, Machine learning, KNN, Feature extraction, Noise reduction, Clustering, Regression algorithms, Classification.**

I. INTRODUCTION

E-Nose is an electronic gadget that might identify and perceive various scents, and gases, similar to a human nose. Despite the fact that it isn't quite as touchy as the human smell sense, the E-Nose doesn't handily get exhausted, and can distinguish various scents. Current electronic noses are designed for lab-based or standalone applications. Food quality monitoring, gas leakage detection, explosives detection, and drugs detection are examples of E-Nose applications. To get to the example forecast results, the client should be where the E-Nose is found.

E-Nose creates its distinctive aroma pattern by employing a non-specific chemical sensor array. Machine learning performance can suffer as a result of the array's high computing load, increased data volume, high energy consumption, and high number of sensors [1].

The E-Nose works through a mix of sensor arrays and different pattern recognition models, permitting it to make special "scent profiles" for various substances. These profiles are then contrasted with datasets of known smells to distinguish and evaluate the recognized fragrance [2]. Industries like food and drink, natural observing, horticulture, and medical services have profited from E-Nose innovation. E-Noses can, for instance, evaluate the freshness of ingredients, spot spoilage, and guarantee product quality in food production. Natural applications include distinguishing contaminations and destructive gases, while farming advantages from illness and irritation discovery in crops. In addition, the medical services area finds utility in diagnosing ailments through the recognizable proof of explicit breath smells [3]. The E-Nose concept is depicted in Fig. 1. E-Nose creates its distinctive aroma pattern by employing a non-specific chemical sensor array. In the designing

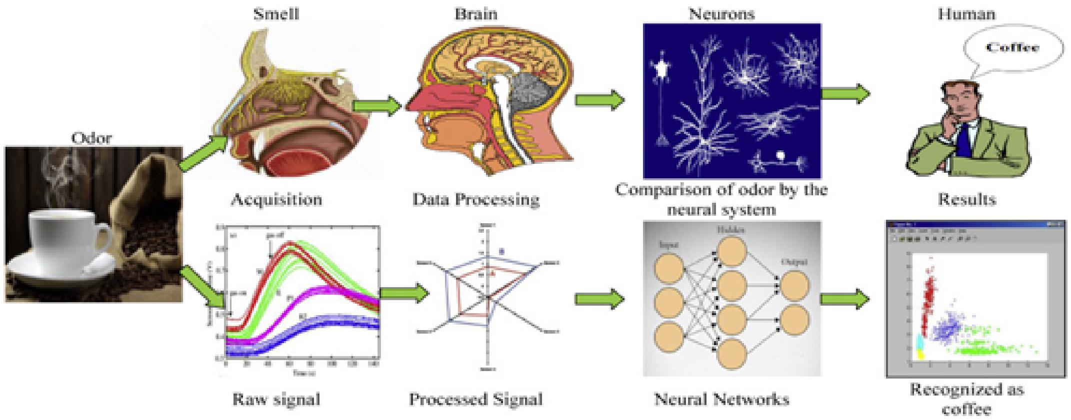

Figure 1: E-Nose concept [4].

process of E-Noses; overuse of sensors can potentially negatively impact machine learning performance, needing more processing power and computational requirements, too much data to deliver, and consumes a lot of energy. This is in opposition to the attributes of the Internet of Things (IoT) infrastructure, which has limited resources. Sensor exhibits advancement methods can be utilized to defeat these issues. In electronic olfactory research, Metal Oxide Semiconductor (MOS) is the most commonly used form of synthetic sensor [5]. Based on previous research, the E-Nose device adds to the model recognition framework by using the voltage (V) value or the electrical resistance (R) value provided by the MOS sensor. They do not make use of MOS sensors, which have the ability to identify various unanticipated natural mixes.
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, section II presenting the study and survey on recent E-Nose and smell detection systems. The methodologies of this work are presented in section III. Section IV presents the current results. Finally, the conclusion and future work are discussed in section V.

II. LITERATURE REVIEW

This section presents the recent frameworks and utilizations of E-Noses based on sensor arrays. The works contemplated are 2020, 2021, and 2023.
Research studies have shown the capability of E-Nose sensors array innovation in different fields like food and refreshment industries, medical diagnosis, monitoring, security, and defense. In the food business, array sensors have been utilized for the discovery of food decay and tainting, identification of food fragrance and flavor, and assurance of food quality.

In medical diagnosis, E-Noses have been utilized for the recognition of illnesses like lung cancer, diabetes, and urinary infectious diseases. In natural monitoring, E-Noses have been utilized for the recognition of air contamination and perilous synthetic substances. In security and defense, E-Nose sensors have been utilized for the recognition of explosives and the distinguishing proof of unsafe synthetics.

Mansour Rasekh, et al. (2021) [1]. To further develop general framework activity and adequacy in separation and arranging unstable medicinal ointments obtained from natural eatable plants fruit, an E-Nose system using performance-analysis methods was evaluated. An E-Nose (MAU-9 electronic-nose framework) furnished with nine Metal Oxide Sensors (MOS) was utilized. MQ-9, MQ-4, MQ-135, MQ-8, TGS2620, MQ-136, TGS813, TGS822, and MQ-3, were used for this system. Using Artificial Neural Network (ANN) classification, Kohonen networks, Learning Vector Quantization (LVQ), and Multilayer Perceptron (MLP) were used to classify E-Nose data. Furthermore, the ability of each metal oxide semiconductor sensor component in the E-Nose sensor array to discriminate between Volatile Organic Compounds (VOCs) analyzed in the headspace and pure essential oils were assessed. Two computations have been considered: Partial Least Squares (PLS) and Principal Regression (PR). All factual techniques with high exactness have been tested and classified the essential oils. Smell characterization with the PLS technique accomplished a lot higher exactness with two ideal MOS sensors than utilizing all sensors. ANN two-group and six-group classifications of essential oils were respectively 100% and 98.9% accurate.

Farel Ahadyatulakbar Aditama, et al. (2020) [6]. An E-Nose framework prototype for Gyrinops versteegii agarwood classification was developed. Three gas sensors TGS822, TGS2620, and TGS2610 were used in this work. To control information obtaining and quality characterization of the e-nose framework, the algorithm of ANN backpropagation has been utilized with the Arduino microcontroller module. The sensor framework capabilities as an acquisition gadget that measures the objective gas fixation based on the value of the ADC converter which is perused by the sensor. The framework converts data on the ADC value into outcomes as the agarwood quality based on the categorization of the ANN. The type of agarwood can be identified by the electronic nose framework. The characterization result for the low-quality agarwood is [-1 1], whereas the grouping result for the high-quality agarwood is [1 -1].

Jin Wang, et al. (2021) [7]. Tea aroma detecting based on E-Nose sensor array using correlation coefficient and cluster analysis was proposed. In terms of reducing the number of sensors (redundant sensors), correlation coefficient and Distinguishing Performance Value (DPV) has been calculated. Cluster analysis was used to obtain sensor independence. According to the following criteria, array sensor is constructed: Sensors delicate to fragrance parts, sensors utilized in different examinations concerning smell location, additionally, sensors with consistent performance and a wide range of models. The gas sensors were ultimately chosen based on these three criteria. The optimized sensor array LG overlaps two types of tea areas when distinguishing twelve different varieties of green tea utilizing the LDA-ave, LDA-var, and PCA-ave approaches. Joined with the NNC calculation, the precision can reach (83.33-94.44)%. The proposed E-Nose strategy can wipe out repetitive sensors and work on the nature of unique tea smell information. Less sensors could not just stop the decrease of the sensor at any point cluster's presentation in tea smell discovery however can likewise further develop it; this is because the presentation of clamor is diminished.

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Borowik, P, et al. (2021) [8]. Recognition of Pathogenic Fungi was created utilizing two developments of a minimal expense E-Nose. The principal planned E-Nose utilizes six vague Figaro Inc. metal oxide gas sensors. Ten sensors from just two types (TGS 2602 and TGS 2603) operating at different voltages are used in the E-Nose. Logistic regression strategy based machine leaning models were made. Ten temperature, humidity, and metal oxide gas sensors (TGS) were used in the construction of the E-Nose device. They have used TGS 2602 (sensitive to ammonia, volatile organic compounds, and H2S) and TGS 2603 (sensitive to amine and sulphur series scents). To visualize information conveyance schemes and transform the info dataset into a less layered space, Principal Component Analysis (PCA) is utilized. Every analysis of the trial data that was released was carried out using the scikit-learn module, which is based on Python code. The highlights that were distinguished from the reaction bends of the sensor represented the PCA contribution. The elements selected by the categorization models considered the differences between the sample categories. The sole purpose of the PCA analysis was to reduce the dimensionality of the problem, which aided in information perception.

Peng, Z. et al. (2023) [9] provided a thorough assessment model for the sensor array optimization of E-Nose devices. The PCA contribution rate and several other evaluation criteria serve as the foundation for the proposed model. The model tried to utilize an information from an E-Nose framework intended to recognize three sorts of tea. The outcomes demonstrate the way that the proposed model can streamline the sensor array and work on the presentation of the E-Nose framework. The review presumes that the proposed model can give a functional manual for the improvement of array sensors in E-Nose frameworks. The authors investigated a dataset of eight kinds of gases utilizing five distinct sensors, and the outcomes showed that the proposed assessment model can assess the exhibition of various sensor arrays and select the ideal sensor exhibit for explicit applications. The proposed model can also be used to design and improve sensor arrays for other purposes, like monitoring the quality of food, the environment, and medical diagnosis. Generally speaking, the research gives a helpful way to deal with upgrading the sensor array of electronic noses and working on their presentation in different applications.

John et al. (2021) [10] provided 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.

Tan et al. (2020) [11] 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.

Huang et al. (2022) [12] 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.

Terutsuki et al. (2021) [13] presented a novel approach to efficient odor source localization using a small bio-hybrid drone. Their research aimed to tackle challenges in identifying and localizing odor sources, vital for applications like environmental monitoring and search and rescue operations. By combining multiple sensors and navigation strategies inspired by insect behavior, the bio-hybrid drone efficiently detected and navigated toward odor sources, showcasing the potential of this approach in complex environments.

Borowik et al. (2020) [14] 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.

Meléndez et al. (2022) [15] presented a portable E-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 shows the potential of electronic noses in addressing specific quality issues in various applications.

Tong et al. (2022) [16] concentrated 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.

Shigaki et at. (2018) [17] designed and made an 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 E-Nose to a small quadcopter, enabling it to detect and track odors in the environment. The study shows the potential of such devices in various applications, including environmental monitoring, search and rescue missions, and agricultural surveillance.

Advances in electronic smell have the potential to revolutionize a variety of sectors and solve urgent problems as this field develops. This paper offers the empirical analysis in Table I.

III. METHODOLOGY

A. *Array Sensors and Measurements*

The proposed E-Nose sensors array, system architecture, and the proposed model will be discussed in this section. Fig. 2 indicates the proposed system architecture. The design of an E-Nose started by choosing the tools and components needed. In this study, it has been used an Arduino microcontroller (MEGA 2560), 6 gas sensors, and humidity sensor placed on designed tubular base. A list of components and E-Nose circuit schematic can be seen in Fig. 3. Gas sensors from the MQ series, such the MQ-2, MQ-4, MQ-8, MQ-135, and MQ-136 are appropriate for gases since they can measure

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TABLE I
Comprehensive Analysis of The Current Researches

Author et al.	Sensor Used	Methodology	Algorithm Used	Results	Output
Rasekh et al. [1]	MAU-9 electronic-nose MOS sensor array	"Performance analysis of MAU-9 electronic-nose MOS" sensor array components and ANN classification methods for discrimination of herb and fruit essential oils"	ANN	Accuracy 91%	Discrimination of different types of herb and fruit essential oils
Aditama et al. [6]	MOS sensors	Artificial Neural Network (ANN)	Backpropagation	Accuracy 91%	Classification of lombok agarwood
Wang et al. [7]	MOS sensors	Correlation coefficient and cluster analysis	KNN	Accuracy 92%	Classification of tea aromas
Borowik et al. [8]	MOS sensors	Artificial Neural Network (ANN)	Backpropagation	Accuracy 90%	Detection of pathogenic fungi
Peng et al. [9]	MOS sensors	Comprehensive evaluation model	SVM	Accuracy 94%	Optimization of sensor array
John et al. [10]	"Chemiresistive sensor-based"	Recent advances in chemiresistive sensor-based e-nose systems for food/environment monitoring	SVM	Accuracy 94%	Detection of different types of food and environmental contaminants
Tan et al. [11]	MOS sensors and taste sensors	PCA and discriminant analysis	SVM	Accuracy 95%	Determination of food quality-related properties
Huang et al. [12]	MOS sensors	Principal Component Analysis (PCA)	SVM	Accuracy 98%	Identification of 10 industrial gases
Terutsuki et al. [13]	MOS sensors	Odor concentration and direction recognition	KNN	Accuracy 95%	Localization of odor sources
Borowik et al. [14]	MOS sensors	Reduced sensor array	PCA	Accuracy 88%	Odor detection
Meléndez et al. [15]	Digital and analog chemical sensors	Portable e-nose for 2,4,6-Trichloroanisole discrimination	KNN	Accuracy 95%	Discrimination of 2,4,6-Trichloroanisole from VOCs
Tong et al. [16]	Electronic Nose Sensor Array	Design and optimization for real-time vehicle exhaust pollutant detection	SVM	Accuracy 93%	Detection of different types of vehicle exhaust pollutants
Shigaki et al. [17]	Odor sensing on a quadcopter	Design and experimental evaluation of a a method for quadcopters	KNN	Accuracy 95%	Detection of different types of odors

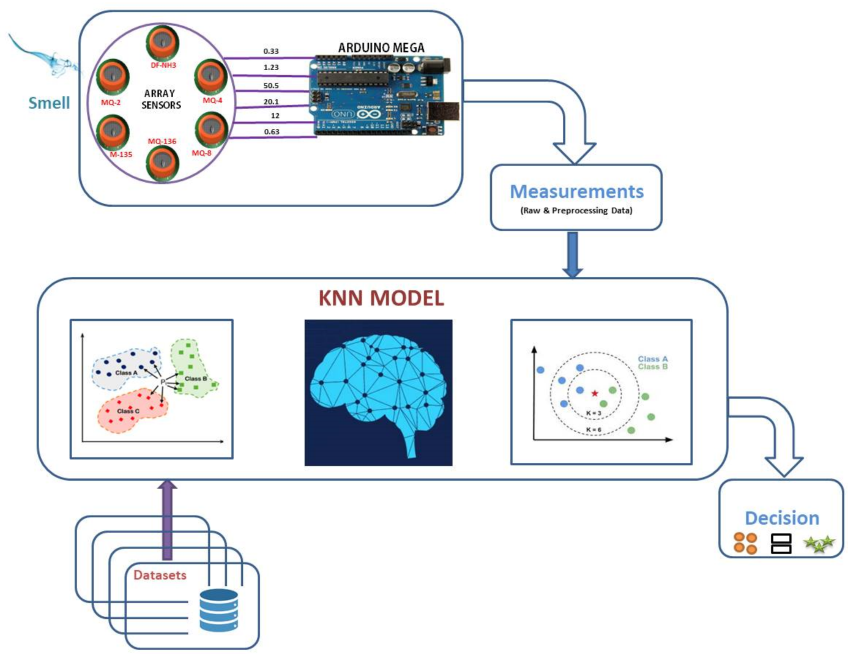

Figure 2: System Architecture.

the concentration of gases in the air and provide values as analog voltages. There are multiple procedures involved in determining the gas concentration in the air using MQ sensors. First, using equations (1) and (2) to compute the sensor resistance value Rs when exposed to gas.

$$Rs = \left(\frac{VC - VRL}{VRL}\right) \cdot RL \tag{1}$$

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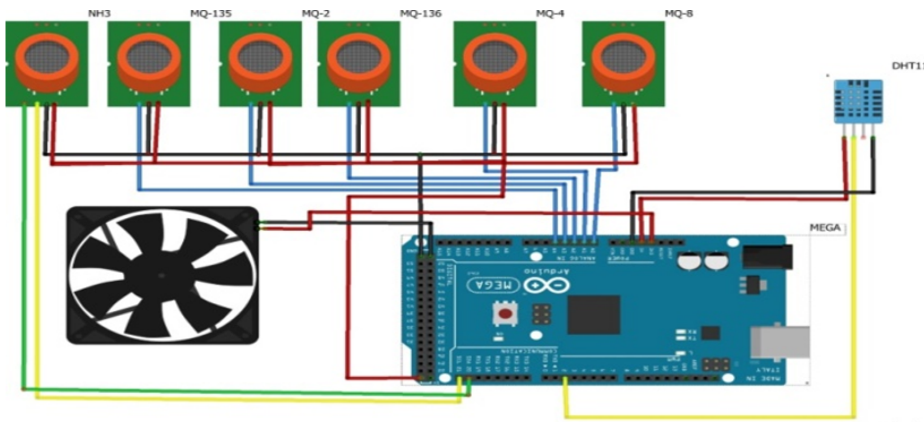

Figure 3: E-Nose circuit diagram.

$$VRL = \frac{V_C \cdot ADC}{1023} \tag{2}$$

Where VRL is the sensor voltage when exposed to a gas, Vc is the voltage value on the Arduino measured by a multimeter, and RL is the sensor resistance value taken from the sensors datasheet. ADC represents the (10 bit) analogue to digital conversion gained from Arduino. Equations (3) and (4) can be used to determine the gas concentration in parts per million (ppm) once the Rs has been computed by:

$$C = A \cdot \text{Ratio}^B \tag{3}$$

$$\text{Ratio} = \frac{Rs}{Ro} \tag{4}$$

The sensor resistance value in clean air, free from gas exposure, is denoted by Ro, and it can be found on the datasheet of every MQ gas sensor. A and B are the correlation coefficients values of the sensors in clean air and these calculated using the datasheet figures of each sensor and nonlinear regression. The sensor resistance should be read at a specified amount of ppm in order to determine the Ro value, which is needed in order to use the correlation function for various gases. Ro can be found by using equation (5).

$$Ro = Rs \cdot \left(\frac{A}{\text{ppm}}\right)^{\frac{1}{B}} \tag{5}$$

Table II shows correlation coefficients values A and B of the used sensors in clean air. Using the parameters and equations above, Arduino is then programmed to take measurements of different odors for 4-6 minutes with two intervals of reading per second. Exhaust fan is used for both; collect the odors from the sources and clean the sensors chamber. The Arduino is programmed to send data via a USB cable to the PC / Laptop and export them as CSV file. CSV file of the readings can be obtained using PLX-DAQ software. The collected data include (time, date, temperature, humidity, VRL, Ratio, and ppm) of each sensor used further to feed the classification model as a dataset.

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TABLE II
Correlation coefficients values in clean air

Sensor	A	B
MQ-136	36.737	-3.536
MQ-135	102.2	-2.473
MQ-8	976.97	-0.688
MQ-4	1012.7	-2.786
MQ-2	574.25	-2.222

B. *K-Nearest Neighbor (KNN) Algorithm*

KNN is a non-parametric method that uses similarity to classifying new data points. It makes the assumption that 'k' nearby data points with comparable qualities is present near to one another and exhibits a comparable pattern. Applications for KNN exist for multiclass problems with classification. It is appropriate for a variety of datasets because it can classify outputs into several classes. To implementing KNN; number of neighbors (k) and scikit-learn library should be chosen for efficient implementation in Python. In this application, it can be employed to predict a specific type or concentration of gas or scent based on new measurements if the dataset containing labeled cases of gas concentrations. Euclidean distance is a key mathematical concept of KNN algorithm. Given two points $P(a_1, b_1)$ and $Q(a_2, b_2)$, the Euclidean distance between them is given in equation (6) (two dimensions space).

$$\text{Distance} = \sqrt{(a_2 - a_1)^2 + (b_2 - b_1)^2} \tag{6}$$

The Euclidean distance for a multidimensional space with features $a_1, a_2, \ldots, a_n$, given in equation (7).

$$\text{Distance} = \sqrt{\sum_{i=1}^{n} (a_{2i} - a_{1i})^2} \tag{7}$$

An overview of how to utilize KNN for gas or smell detection is provided below:

1) Data Collection: Create a dataset containing measurements of gas concentrations and labels that identify the type of gas or the concentration at which it is present. In this study, the data collected from each sensor readings include; (time, date, temperature, humidity, VRL, Ratio, and ppm) of each sensor used further to feed the classification model as a raw dataset. Many samples have been used for data collection (Natural Air, Gasoline, Petrol, and Colonia).

2) Data Preprocessing: Prepare and organize the data. This could involve sorting the dataset into training and testing sets, addressing missing values, and normalizing the data. In this case study it has not applied any optimization or data preprocessing technique to extract the features from raw data.

3) Feature Selection: Determine which important features such as sensor readings, the surrounding environment, etc. will be fed into the model. In this case study, the features extracted from each sensor readings include (VRL, Ratio, and ppm) is used as earlier stage of this work.

4) Training: Using the training dataset, train the KNN model. The correlations between the input features and the appropriate gas type or concentration will be taught to the model. For more accuracy, features are reduced and fed into

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the model in this stage.

5) Validation and Test: To evaluate how successfully the model generalizes to new, untested data, validation is an essential step. The validation procedure gives you an approximation of the model's performance on data it has not seen during training and aids in fine-tuning hyperparameter like the number of neighbors (k). Train-Test Split, Cross-Validation, Leave-One-Out Cross-Validation (LOOCV), Stratified Cross-Validation, and Parameter Tuning are validation techniques employed to determine how well new data will probably work with the proposed KNN model and use this information to help you decide on its hyperparameters. Evaluate the performance of the trained model on a separate testing dataset. This will give an indication of how well the model generalizes with new unseen data. In the test stage, analyzing the trained model's output on a different testing dataset will show how well the model applies to new, untested data.

6) Prediction: Utilize the learned model for predicting new measurements of gas concentrations and the smells of selected samples. The dataset, sensor readings, selected features, result and accuracy of suggested KNN model mentioned in section IV.

IV. RESULTS

A. *Sensor Readings and Dataset*

The proposed work is resultant an E-Nose prototype which able to monitor air quality and recognition of different odors and smells. The samples chosen in this study were clean air, gasoline, petrol, and perfumes. These types of samples produce different odors. 360 raw data points on the concentration of VOCs were obtained from each sample during the data collecting phase using the intended model. Prior to classification, the ML model KNN was trained using 17 features. The presentation of the proposed KNN model expanded when the features were decreased to 6. Table III shows the details of all features and selected features used to train the machine learning model.

Fig. 4, Fig. 5, Fig. 6, and Fig. 7 show the responses of the sensors when exposed to different odors for the all 17 features.

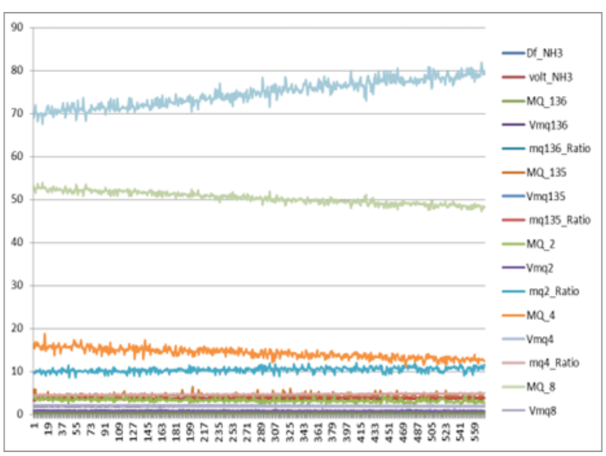

Figure 4: Sensors response in clean air.

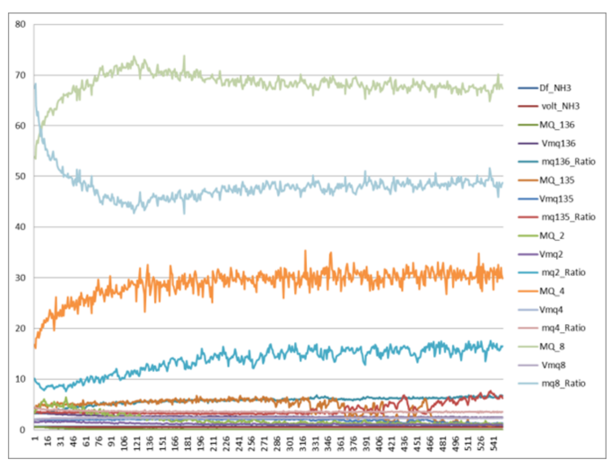

Figure 5: Sensors response when exposed to gasoline.

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TABLE III
Comparison Between 17 Features and 6 Features

No.	17 Features	6 Features
1	DF-NH3 ppm	DF_NH3 ppm
2	DF-NH3 VRL	MQ-136 ppm
3	MQ-136 ppm	MQ-135 ppm
4	MQ-136 Ratio	MQ-8 ppm
5	MQ-136 VRL	MQ-4 ppm
6	MQ-135 ppm	MQ-2 ppm
7	MQ-135 Ratio	
8	MQ-135 VRL	
9	MQ-8 ppm	
10	MQ-8 Ratio	
11	MQ-8 VRL	
12	MQ-4 ppm	
13	MQ-4 Ratio	
14	MQ-4 VRL	
15	MQ-2 ppm	
16	MQ-2 Ratio	
17	MQ-2 VRL	

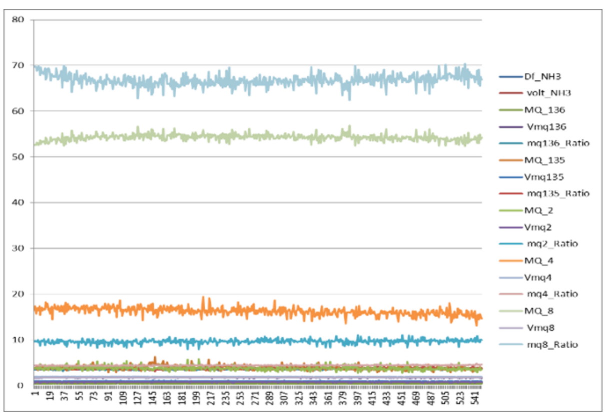

Figure 6: Sensors response when exposed to petrol.

Figure 7: Sensors response when exposed to colonia.

B. Test and Accuracy

The proposed KNN model was tested in two stages. The prior ML model KNN tested by trained all 17 features with 68.2% accuracy. The accuracy is expanded to 71.1% when the features were decreased to 6 in the second stage of testing. Fig. 8, Fig. 9, Fig. 10, and Fig. 11 show the responses of the sensors when exposed to different odors for the selected 6 features.

The minimum and maximum value for each curve of six sensors responses of different odors for the selected 6 features mentioned in Table IV. Table V shows the accuracy of the proposed work when raw data and reduced data used for ML model.

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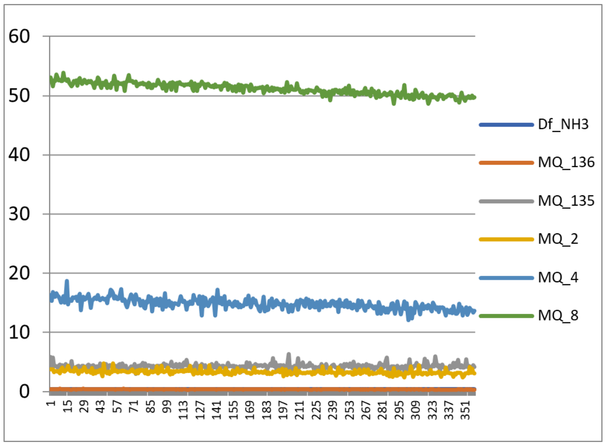

Figure 8: Sensors response in clean air.

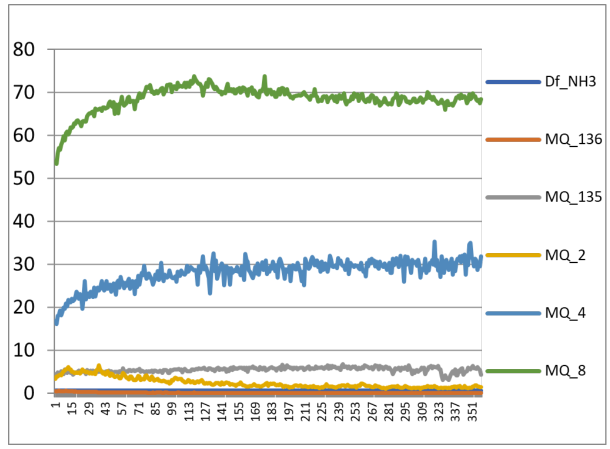

Figure 9: Sensors response when exposed to gasoline.

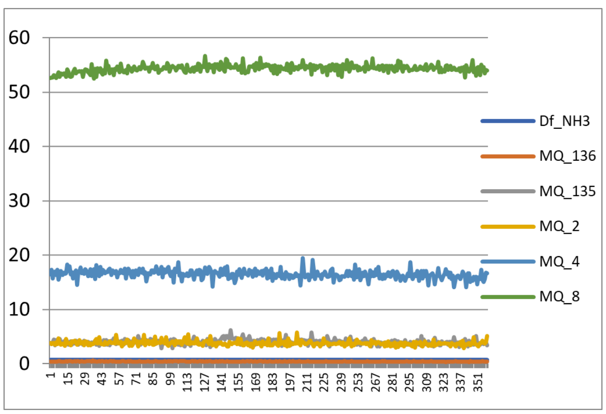

Figure 10: Sensors response when exposed to petrol.

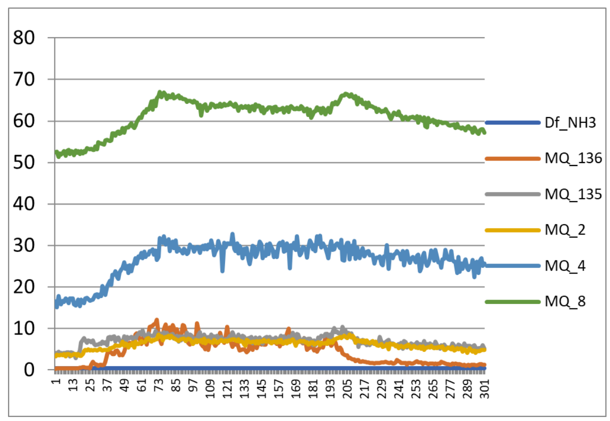

Figure 11: sensors response when exposed to colonia.

TABLE IV
Min-Max Value of Six Sensors Responses

Sensor	**Samples**							
	Clean Air		**Petrol**		**Gasoline**		**Colonia**	
	MIN (ppm)	**MAX (ppm)**	**MIN (ppm)**	**MAX (ppm)**	**MIN (ppm)**	**MAX (ppm)**	**MIN (ppm)**	**MAX (ppm)**
DF-NH3	0.41	0.41	0.69	0.69	0.63	0.63	0.34	0.34
MQ-136	0.30	0.48	0.34	0.61	0.04	0.58	0.33	12.08
MQ-135	2.85	4.97	2.83	6.23	0.67	6.71	2.82	10.39
MQ-8	47.18	52.15	52.36	56.87	53.44	73.84	51.37	66.92
MQ-4	11.18	15.89	13.04	19.43	16.09	35.35	15.16	32.77
MQ-2	2.30	3.88	2.76	5.79	1.10	6.45	3.24	8.47

Based on a combination of sensors selected, the E-Nose product is designed. In this study, the proposed system is configured and programmed as the prototype of a first stage of Ph.D. work on mobile robot for detection and recognition odors based on gas sensors array. The final E-Nose device assembled using array of six sensors seen in Fig. 12.

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TABLE V
Accuracy Comparison of Raw and Reduced Data

Algorithm	**Accuracy**	
	Raw Data (17)	**Reduced Data (6)**
KNN	68.2%	71.1%

Figure 12: Designed E-Nose.

V. CONCLUSION AND FUTURE WORK

The E-Nose sensor array is proposed in this research as a prototype for a potential future smell detection system. The centralization of VOCs serves as the input data for the categorization method. This collection of data can be used to determine which compound is dominant and what mixtures a sample produces. The used dataset is created from the real-time sensor readings for each sample. Using all 17 features from different sensors readings, the proposed KNN model shows 68.2% accuracy in the earlier stage of this work. The KNN algorithm yields an accuracy of 71.1% when six features from six different sensors are used. This work is the first stage of Ph.D. research on intelligent E-Nose for odors detection and recognition. In future, the system will be optimized to get more accuracy using different sensors and algorithm. The core of future work is how to design a special classification method to classify multi-varieties. The final system will be as an intelligent mobile E-Nose for real time smell detection and recognition based on sensors array.

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CONFLICTS OF INTEREST

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