IOT BASED FOOD ANALYSIS FOR VOLATILE ORGANIC COMPOUNDS USING Arduino Uno & MACHINE LEARNING

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UNIVERSITY OF ENGINEERING & MANAGEMENT, JAIPUR

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Approval Certificate

This is to certify that the project report entitled "**IOT BASED FOOD ANALYSIS FOR VOLATILE ORGANIC COMPOUNDS USING Arduino Uno & MACHINE LEARNING**" submitted by **Diganta Sengupta**(Roll:**12019002002010**) in partial fulfillment of the requirements of the degree of **Bachelor of Technology** in **Electronics & Communication Engineering** from **University of Engineering and Management, Jaipur** was carried out in a systematic and procedural manner to the best of our knowledge. It is a bona fide work of the candidate and was carried out under our supervision and guidance during the academic session of 2019-2023.

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Diganta Sengupta

ABSTRACT

An instrument designed to imitate the human sense of smell is called an electronic nose. An array of chemical gas sensors, a sample handling system, and a pattern recognition system are used in electronic noses (e-noses). Pattern recognition gives the system more selectivity and reversibility, which opens up a wide range of applications. These include environmental monitoring and process control, as well as the medical and food industries. There are numerous additional gas sensors available. Conducting polymers (CP), metal oxide semiconductors (MOS), piezoelectric, optical fluorescence, quartz crystal microbalance (QCM), and amperometry gas sensors are some examples of these. Reliability, robustness, sensitivity, selectivity, and reversibility would all characterize the ideal gas sensor. It is hard to achieve high selectivity and reversibility. After signal handling and element extraction the result of the sensors give an interesting "smell print" for that substances which can be utilized to arrange, measure fixation, or confirm quality. This paper looks at how the electronic nose works, how it can be used, and how well it can be used to detect gases with a certain smell that are caused by volatile organic compounds (VOCs) like ethanol, acetone, and benzene at different concentrations. The Electronic Nose is a dependable instrument that can be used for environmental control (air quality, pollutants, and gas emission levels), medical science (urine, skin, and breath odor, etc.), and other applications. industry of food (milk, coffee, soft drinks, fish, meat, etc.), pharmaceutical, chemical, defense, and security industries (for example, detecting humanitarian land mines) and manufacturing procedures for semiconductors.

The study focuses on monitoring freshness and determining food spoilage for the human health. The objective is to design an electronic nose system that will be sensitive to the gases emitted by spoiled food samples namely banana, peachy, carrots and grapes operating in room temperature to observe the degree of spoilage for 3 days and then determine food spoilage. To consider the capability of electronic nose for freshness and milk spoilage detection, the odor pattern was analyzed using machine learning model Non-Linear SVC with the accuracy of around 70% respectively have been used to classify the data. Food wastage dew to spoilage is one of the key global problems, the quantity of food loses and spoilage per year is 40-50% for root crops, fruits, and vegetables. This paper proposes an edge IoT & machine learning based approach for food quality monitoring. The need for this type of system is to correctly classify the vegetables and fruits in two categories semi-fresh & spoiled. The proposed system employed with Arduino Uno as the main processing unit, coupled with three VoC gas sensors. To classify the fruit, as in our work banana was considered as the target fruit, the sensed data (Gas Sensors MQ7 & MQ3 were collected over a period of three days. The uniqueness of the system is, it uses edge IoT and its software is programmable so that it can be used to preserve any type of food items.

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1. CHAPTER

INTRODUCTION

1.1 Volatiles of the Edibles

Aroma (odor) plays a crucial role in the creation of novel food products [1]. Thus, the primary objective of many studies is to characterize aroma. Smell portrayal can give information in the space of food items' quality and their relationship to buyers' decisions [2]. Identifying key molecules that account for the aroma characteristics of particular food products is frequently accomplished through the aroma evaluation. Organic compounds that are volatile make up most aroma molecules. These mixtures come from, e.g., the aging of plants, the advancement of oils or during normal cycles, for example, maturation [3][4][5][6], yet additionally food defilement [7].

At room temperature, volatile organic compounds (VOCs) are organic compounds with a high vapor pressure. A trait known as volatility, high vapor pressure is related to a low boiling point, which is related to the number of molecules in the air surrounding the sample.[1] VOCs are the ones that cause pollutants to smell like perfumes and scents. Some volatile organic compounds (VOCs) are harmful to human health or the environment, while others serve as attractants for pollinators, protect plants from predators, and even facilitate interactions between plants. Anthropogenic VOCs are managed by regulation, particularly inside, where fixations are the most elevated. The majority of volatile organic compounds (VOCs) are not acutely toxic, but they may have long-term, chronic effects on health. Some VOCs have been utilized in drug store; others are focus of regulatory controls on account of their sporting use. Respiratory, hypersensitive, or resistant impacts in babies or kids are related with man-made VOCs and other indoor or outside air pollutants.[46]

Some VOCs, like styrene and limonene, can respond with nitrogen oxides or with ozone to create new oxidation items and optional sprayers, which can cause tactile disturbance symptoms.[47] VOCs add to the arrangement of tropospheric ozone and smog.[48][49] Wellbeing impacts incorporate eye, nose, and throat bothering; nausea, loss of coordination, and headaches; and harm to the liver, kidneys, and central nervous system [50]. Animals can get cancer from some organics; some are thought or known to cause malignant growth in people. Conjunctival irritation, discomfort in the nose and throat, headache, allergic skin reaction, dyspnea, declines in serum cholinesterase levels, nausea, vomiting, nose bleeding, fatigue, and dizziness are some of the most common signs or symptoms of exposure to volatile organic compounds (VOCs).[51] The capacity of organic chemicals to cause adverse health effects varies greatly, from those that are highly toxic to those that have no known adverse health effects. The degree of exposure and the amount of time spent in that environment will both have an impact on health, just as they do with other pollutants. Some people have experienced immediate symptoms such as irritation of the eyes and respiratory tract, headaches, dizziness, visual disorders, and memory impairment shortly after exposure to some organics. As of now, not much is been aware of what wellbeing impacts happen from the degrees of organics typically tracked down in homes.

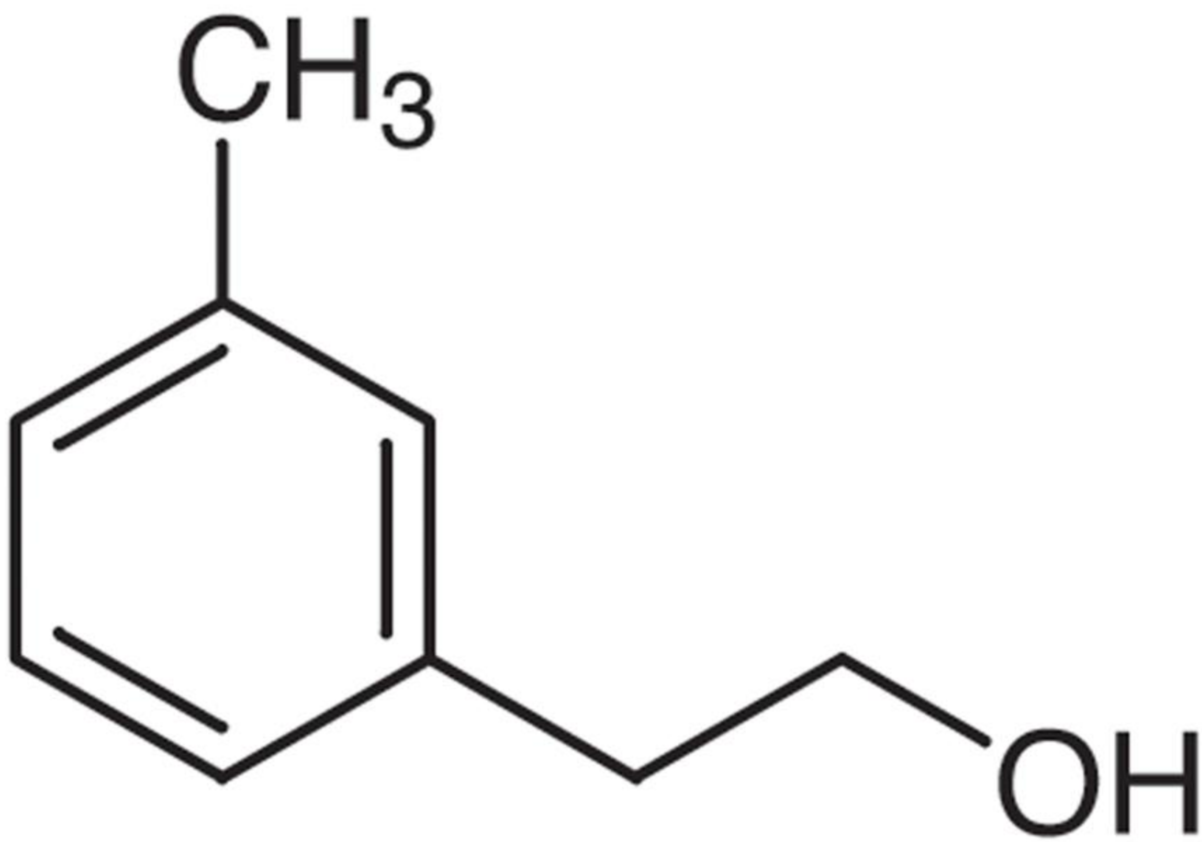


Figure 1 2-(m-Tolyl)-ethanol, a primary VOC found from ripped banana

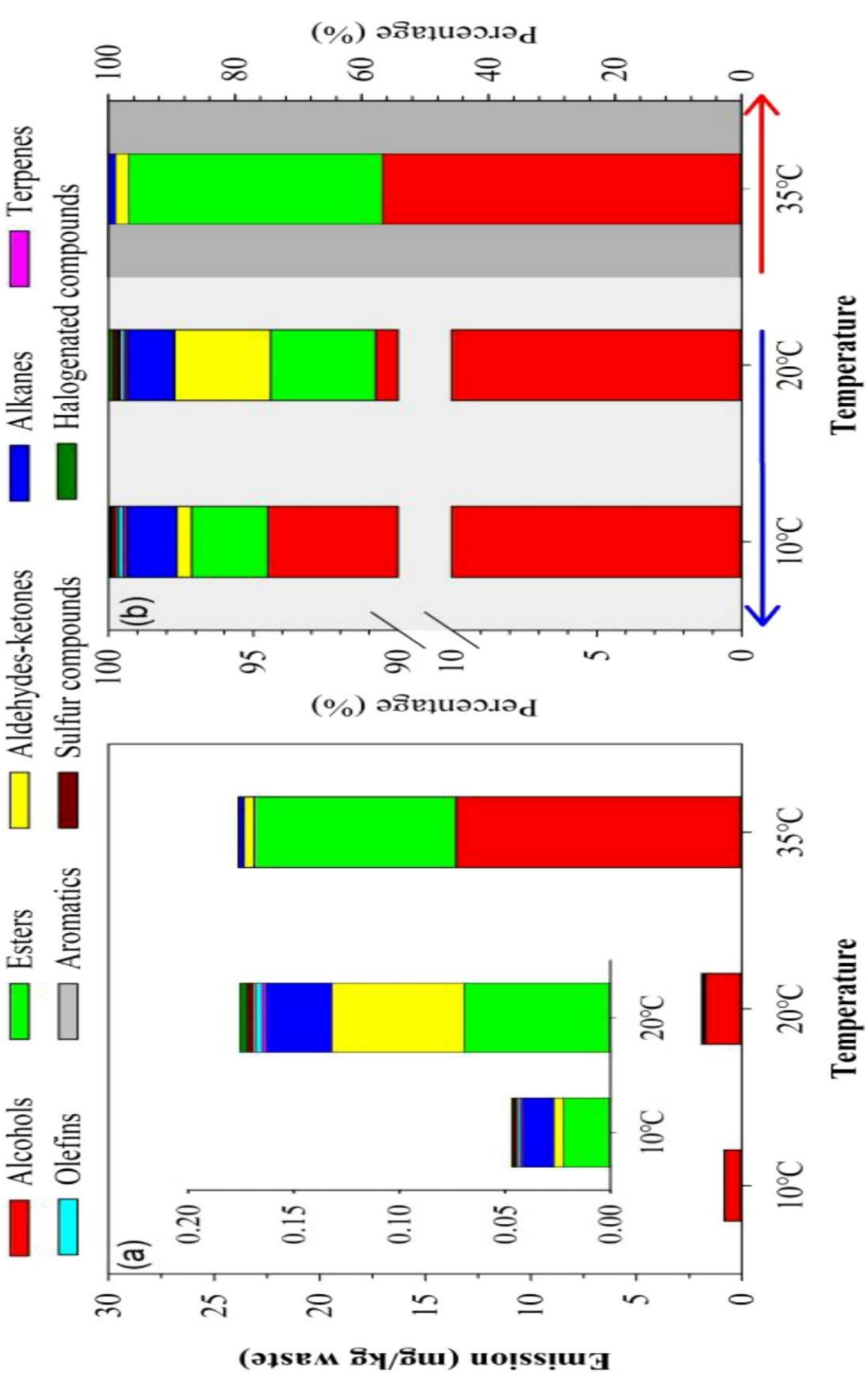


Figure 2 Emissions (mg/kg waste) and the proportion of each compound category of VOCs

It is necessary to understand the mechanism of VOCs release from decomposition of fruit caused via factors such as weather, temperature, moisture, carbohydrate accumulation, and fungal infections; as well as the sources and functions of VOCs, which would contribute to the early detection and monitoring of fruit diseases after harvest and to reduce harm to consumers. The fragrant properties of banana are significant for its engaging quality as a new natural product. The flavor of bananas is pleasant, and they are widely consumed all over the world. The banana's typical flavor compounds are made in a short amount of time while it is ripening, and the aroma's composition changes at different stages, creating distinctive aroma signatures [11]. There have been a few studies on the banana aroma compositions during ripening [11,12], but most of them focused on the chemical aroma compositions during the mature period or during fruit processing. It has also been reported [13] that the composition of aromas shifts at various stages of fruit ripening, which aids in comprehending the formation of aromatic compounds. The distinct flavors of various banana cultivars are due to differences in the predominant volatile components. For instance, the Cavendish cultivar's predominant ester is the volatile component 3-methylbutyl butanoate [14]. Esters typically impart a fruity aroma [7]; For instance, isoamyl butanoate, 3-methylbutyl acetate, and isoamyl isovalerate all play a role in the fruity smell of the banana [15,16]. Although 246 volatile compounds, including 112 esters, 57 alcohols, 39 acids, 10 aldehydes, and 10 ketones, were found in banana fruit, only 12 compounds were found to be significant contributors to the aroma of bananas [16]. Fruit is an essential part of a healthy diet because it is high in vitamins, minerals, fiber, and other nutrients. Individuals smell natural product prior to choosing whether to purchase since organic product fragrance is a sign of natural product quality and development. Even though different fruits have different aroma profiles, the volatile organic compounds (VOCs) of newly harvested and mature fruit are mostly made up of esters, alcohols, aldehydes, ketones, lactones, and terpenoids. In 1939, Gerhardt and Ezell analyzed the volatiles in the apple storage chamber and found that fruit was more likely to release VOCs when Penicillium and Botrytis were infected. In 1941, Biale and Shepherd observed that more VOCs were transmitted from citrus organic product after Penicillium digitatum contamination. Due to the limitations of the extraction and detection techniques of the time, very few reports were published. Headspace solid-phase microextraction, gas chromatography–mass spectrometry, gas chromatography–olfactometry, headspace fingerprint mass spectrometry, and other technologies made significant contributions to VOC research by 1990. Certain volatile organic compounds (VOCs) from infected fruit may function as signaling molecules, contributing to the promotion or inhibition of fungal colonization and the development of fruit resistance to fungal infections. Additionally, certain VOCs from infected fruit may cause skin allergies, gastrointestinal disorders, respiratory tract infections, and asthma, all of which pose serious threats to human health. Through a series of biochemical pathways, fruit volatile organic compounds mostly derive from carbohydrates, fatty acids, and amino acids. Invasion of fungi, temperature, humidity, and so on increases the synthesis of fatty acids, amino acids, and sugars as well as promoting the release of ethylene, which accelerates fruit ripening. Additionally, fungal infections encourage the conversion of these substrates into volatile organic compounds (VOCs) by increasing the activity of enzymes involved in their biosynthesis. An important plant hormone is ethylene. In bananas and numerous different organic products, creation of ethylene floods when the organic product is prepared to age. A dull, hard, green fruit is transformed by this surge into a tender, colorful, sweet fruit that is ready to eat. The primary objective of this project is to identify and compile data on the volatile organic compounds (VOCs) released in the absence of ethylene, another BVOC, during various stages of banana ripening.

1.2 SPME as a Method of Extraction

The SPME procedure depends on the gap of harmony of the analytes between the removed grid and extraction stage, for example, the objective organic product fiber [44]. Direct immersion (DI) or head-space (HS) exposure options exist for the SPME fiber [42]. The analytes are thermally desorbed at the GC injection port before being transferred to the chromatographic column with a carrier gas for separation [45]. Concerning extremity of synthetics, various kinds of coatings may be executed for extraction, for example, polyacrylate covering (Dad), carboxin (Vehicle), polydimethylsiloxane (PDMS), polydimethylsiloxane-divinylbenzene (PDMS/DVB), divinylbenzene-carboxin-polydimethylsiloxane (DVB/Vehicle/PDMS), or with one more sort of sorbents. The outcome of the SPME technique may be associated with its timesaving component and potential choices for automatization, as well as non-solvents use [46]. The fact that multiple steps of analysis can be covered by using SPME, including sampling, separating compounds of interest from other matrix compounds, transferring analytes from the outside to the laboratory, and transporting analytes to the instrument, is a positive feature. The SPME was introduced into numerous applications in cannabis, environmental, forensic, and food analysis. The SPME was introduced into numerous applications in cannabis, environmental, forensic, and food analysis.

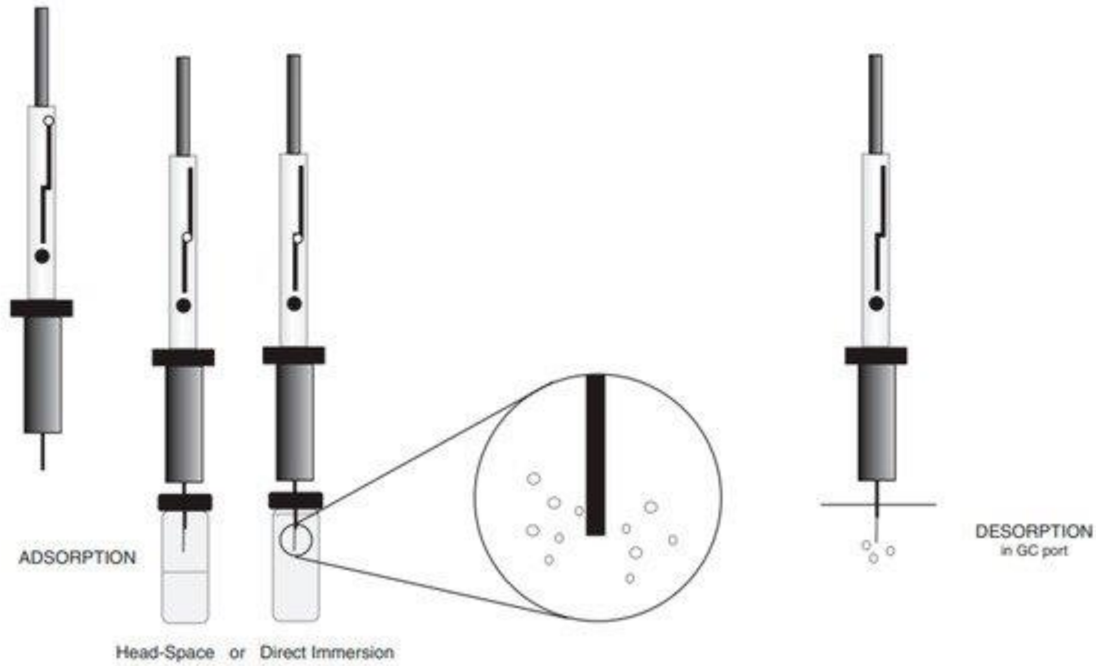


Figure 3The Scheme of the SPME TECHNIQUE

The main five classes of food products that the SPME was implemented for aroma analysis are beverages, dairy, fruits/vegetables, honey, meat, seafood, and wine. the main problems that were solved by using SPME are: studies of volatiles in different varieties of food products, profiling individual molecules reliable for food aroma, categorization of foodstuffs, also proof their authenticity, analysis of particular compounds responsible for food quality, to screen the technological process influences on aroma properties, screening chemical and biochemical processes related to transformations of aroma molecules, and to linked SPME with gas chromatography-olfactometry (GC-O) to describe the characteristic aroma of volatiles extracted by the coating of the fiber. In spite of these advantages that SPME provides, Souza-Silva et al. 47] listed a few of the drawbacks of using SPME for food analysis, such as (1) the limited number of commercially available coatings, (2) the relatively low operating temperature due to the poor thermal stability of coatings, and (3) the de-stability and possible swelling of the coating by organic solvents; and (4) the relatively brief period of coating use.

1.3 The SBSE Extraction

SBSE is a green extraction method that only requires a small number of samples and does not use organic solvents. It could be useful for evaluating various foodstuffs' aroma components. When compared to the SPME method, the extraction capacity of SBSE is superior. Between 50 and 250 times more coating is used in SBSE than in SPME [68]. While SBSE is designed to extract semi- and volatile compounds from the matrices of aqueous foods, the magnetic bar of SBSE is primarily coated with PDMS fiber. Thus, the stir bar is directly inserted into the medium and rotated, capturing molecules before being desorbed by the gas or liquid phase. The other is the headspace sorptive extraction—HSSE—in which the volatile compounds are adsorbed onto the PDMS stirring bar for some time. The ability to extract molecules with a low polarity is the primary advantage of using a coating bar in both extractions. Because SBSE has a very low limit of detection (LoD), it was used to describe things like wine off-flavors [70]. GC equipment is also used with the SBSE method, but because it is not automated, it is not as common as SPME fiber extraction. Franc and others 70] showed high reproducibility and repeatability, and a decent relationship of SBSE as opposed to SPME and fluid extraction (LLE), in the wines' off-flavors profiling. Franc et al. [with SBSE] 70] effectively extricated and evaluated eight area volatiles, which is similarly exceptionally answerable for the horrendous smell of wines for example geosmin with trademark sloppy and stale smelling scent. Ruvalcaba et al. also used SBSE and HSSE to alter the aroma composition of beer samples [59]. In order to establish the authenticity of Spanish brandy, the SBSE was successfully validated to determine the volatiles profile of Sherry brandy [71]. In addition, researchers were able to identify safral as the primary volatile compound in cured ham when saffron was added using this extraction method [22]. In addition, Berrou et al.

[58] upgraded the technique for SBSE to remove bacterial metabolites and laid out the 90% recuperation of volatiles. Expect cocktails and meat, SBSE was like Guerrero et al. [72], evaluate the low detection limits for the determination of volatile components in vinegar samples. In another study, limonene was identified as a major aroma compound in squeezed orange juices and commercial samples by validating SBSE with GC-MS [73]. In order to identify the numerous volatiles that could be aroma-active compounds, it may be necessary to use SBSE and SPME simultaneously.

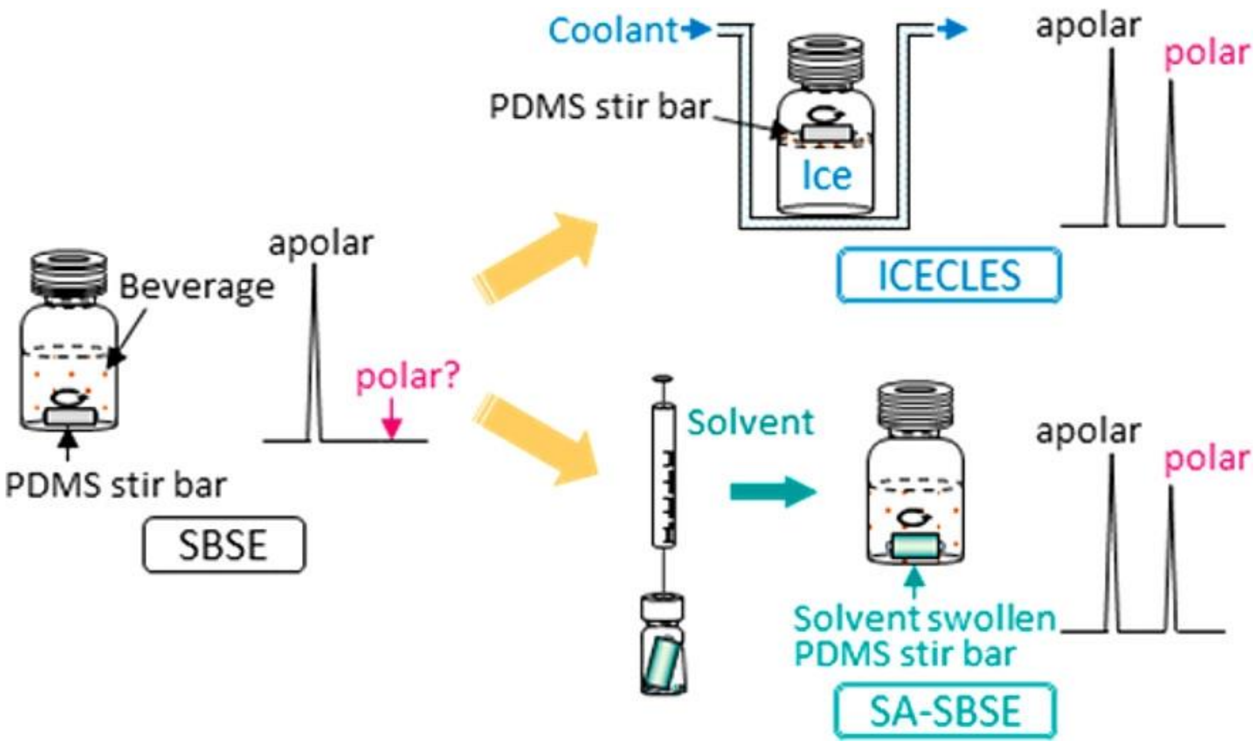


Figure 4 Stir Bar Sorptive Extraction for Food Applications

1.4 Methods of Volatile Compounds Separation and Identification

The separation and identification of volatiles is the second crucial step in the analysis process. SPME has been widely used in a number of different analytical methods: mass spectrometry (MS), capillary electrophoresis (CE), gas chromatography (GC), inductively coupled plasma mass spectrometry (ICP-MS), and ICP-optical emission spectrometry (ICP-OES) [75][76]. Infrequently, volatile compounds were analyzed using liquid chromatography (LC) [77]. In addition, a variety of detectors, such as universal flame ionization (FID) or selective nitrogen-phosphorus (NPD), flame photometric (FPD), and electron capture (ECD) detectors, are utilized. However, the mass detector (MS) is the detector that is utilized the most frequently in the analysis of volatile compounds [75]. MS is an effective method for locating compounds. Using MS, it is possible to keep screening volatile compounds and then compare the obtained mass spectra to the literature or databases that are available. Chin et al., for instance [78] improved the GC-MS method for evaluating the aromas of the majority of popular beverages, such as coffee and wine. Furthermore, Jordán et al. [79], who used the molecular masses of compounds to evaluate the aroma profiles of food products. Singh et al.'s most recent study [80] demonstrated how aroma-active regions of protein-based products can be identified using GC-MS. Due to the fact that many vegan products are not always designed with high consumer acceptability in mind, research into the aroma of protein-rich products is now an important aspect. As a result, knowledge in this area needs to be greatly enhanced. Besides, in light of GC-MS signals, Abou-el-Karam et al. [81] developed the volatile profile database, which can be utilized to verify the authenticity of food. Nicolaï et al. [82] Using chemical standards, they reconstructed the citrus fruit aroma and analyzed its GC-MS profile. In addition to being suggested in extraction practice, miniaturization was also presented by Beck et al. [83] on account of insightful gadgets. Beck and others 83] built portable GC-MS instruments and compared their capabilities to those of benchtop instruments. They thought that using a portable GC-MS was good because it allowed for analysis anywhere. The more recent techniques take less time to perform. Mayr and co. 84] used Proton Transfer Reaction Mass Spectrometry to quickly screen the market for meat's volatiles profile and prevent meat spoilage. Rather than a tedious technique that needs a couple of days to be performed, they applied a strategy that requires a couple of moments. The unstable profile is a mind-boggling blend, which is the reason, frequently, the utilization of GC-MS isn't sufficient to unwind the fragrance of food items. As a result, in order to identify the odor-causing active regions, a set of tools is required. Cialiè Rosso and others [85] described the potent odorants of hazelnuts using two-dimensional GC, whereas Stilo et al. 86] used the volatiles profile of virgin olive oil to create the quality fingerprint. Interestingly, Giri et al. [developed the GCxGC approach] 87] to examine the aroma profile and compounds with toxicology-related properties. Lubes and Goodarzi [61] emphasized the significance of statistical analysis of the obtained data in addition to the requirement for sophisticated analytical equipment. The determination of the food's odor at the time of consumption is also an important factor. Atmospheric-Pressure Chemical Ionization Mass Spectrometry, or APCI-MS, is frequently utilized in this scenario. Elmasry et al. [88] used APCI-MS to determine the authenticity of honey. Ion mobility spectrometry [89] and infrared spectroscopy [90] are two additional analytical methods that have been used to ascertain the volatiles profile. A few methodologies have been taken on to lay out unpredictable profiles in quantitative and semi-quantitative terms and, hence, the outcomes have been communicated in various ways. The outcomes were communicated exclusively as a coordinated pinnacle region, or as a percent commitment of each compound in the aggregate sum of volatiles. This strategy could be utilized exclusively on account of profiling the volatiles in food tests, to decide general contrasts between tests [50]. An internal standard, which may be useful for semi-quantitatively calculating the volatiles content, should be used for the proper study of the content of volatiles [32]. Moreover, the quantitative examination could be performed subsequent to setting up the adjustment bend of norms of every principal unstable, as was completed in the exploration of Starowicz, Koutsidis and Zielinski [33] and Cialiè Rosso et al. [85].

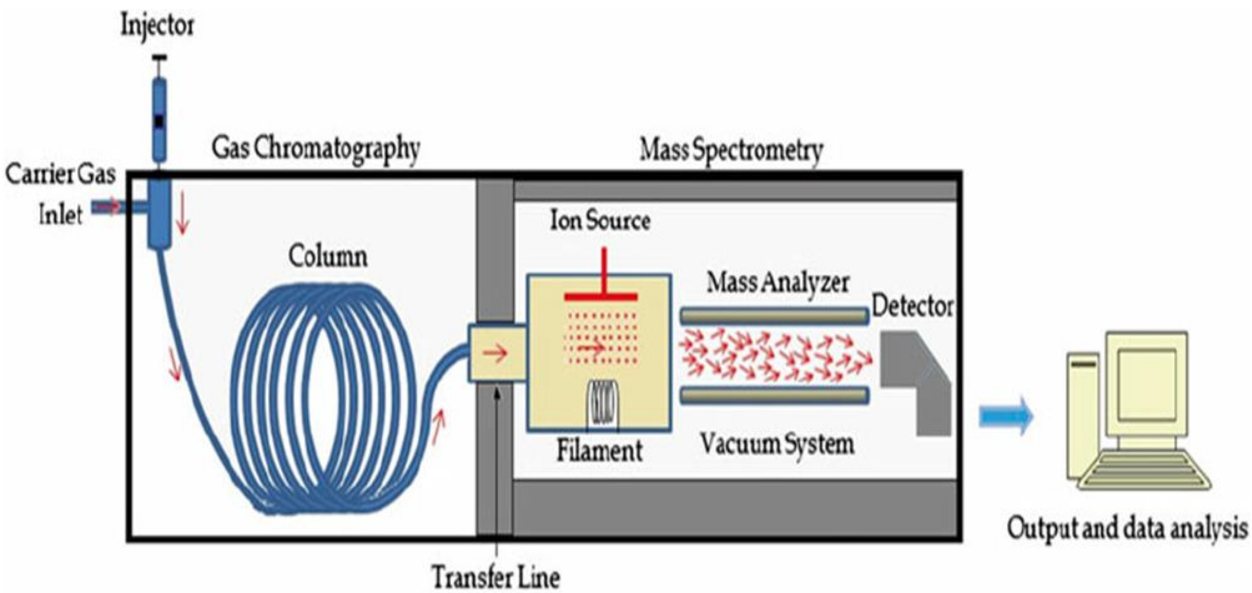


Figure 5 GS-MS setup

1.5 Olfactometry Study

It is common knowledge that the aroma-producing molecules in food staples typically number in the hundreds. Notwithstanding, ~20-30 of these mixtures are vital to produce its fragrance. As a result, it is essential to recognize these compounds that have a significant impact on aroma in order to carry out an important aroma analysis. The most appropriate method in this instance is gas chromatography and olfactometry (GC-O) [92]. The GC-O procedure involves the human nose as a locator that elutes the fragrance from the chromatography segment. In addition, the time, the distinctive aroma quality, and occasionally the intensity are recorded whenever an odor is detected. There are various techniques to assess the general smell capability of the singular fragrance dynamic particle, as fragrance extraction weakening examine (AEDA), Charm Analysis, Osme, and some others [93][94][95]. Remarkably, Feng et al. [96] join AEDA with the SPME method and accomplished agreeable outcomes that permitted to decide the fragrance with tangible effect in Japanese soy sauce. After that, the odor activity value (OAV) (ratio between the concentration of one compound in the food and its threshold concentration) could be determined by detecting and quantifying the odor-active molecules through GC-O analysis. Typically, if one of the compounds has an OAV value greater than 1, it may have an aroma effect on the food product's overall odor. The term "molecular sensory concept" refers to the method of analysis that has been presented. Averbeck and Schieberle [28] demonstrated the off-flavor formation in stored orange juice caused by a significant amount of dimethyl sulfide and 2-methoxy-4-vinyl phenol using this method. In addition, this method made it possible to differentiate the quality of food products that are available on the market [97]. Deuterated standards and/or molecules with carbon isotopically labelled could be used to accurately identify aroma [98]. Sensorial analysis is typically associated with the results obtained during the GC-O methodology. The final stage of the molecular sensory concept is the recombination or omission analysis, during which a professional sensory panel evaluates the aroma as a whole. Kiefl and Schieberle [99] were able to distinguish three hazelnut cultivars using this method, while Ornierczyk and Szumny [100] established the fundamental volatile composition of edible insects and compared it to their sensorial properties and potential consumer acceptance. The compound and tactile association was additionally useful in the height of new items [101]. Sensory panelists, who require specialized training, serve as the primary "analytical tool" in these instances.

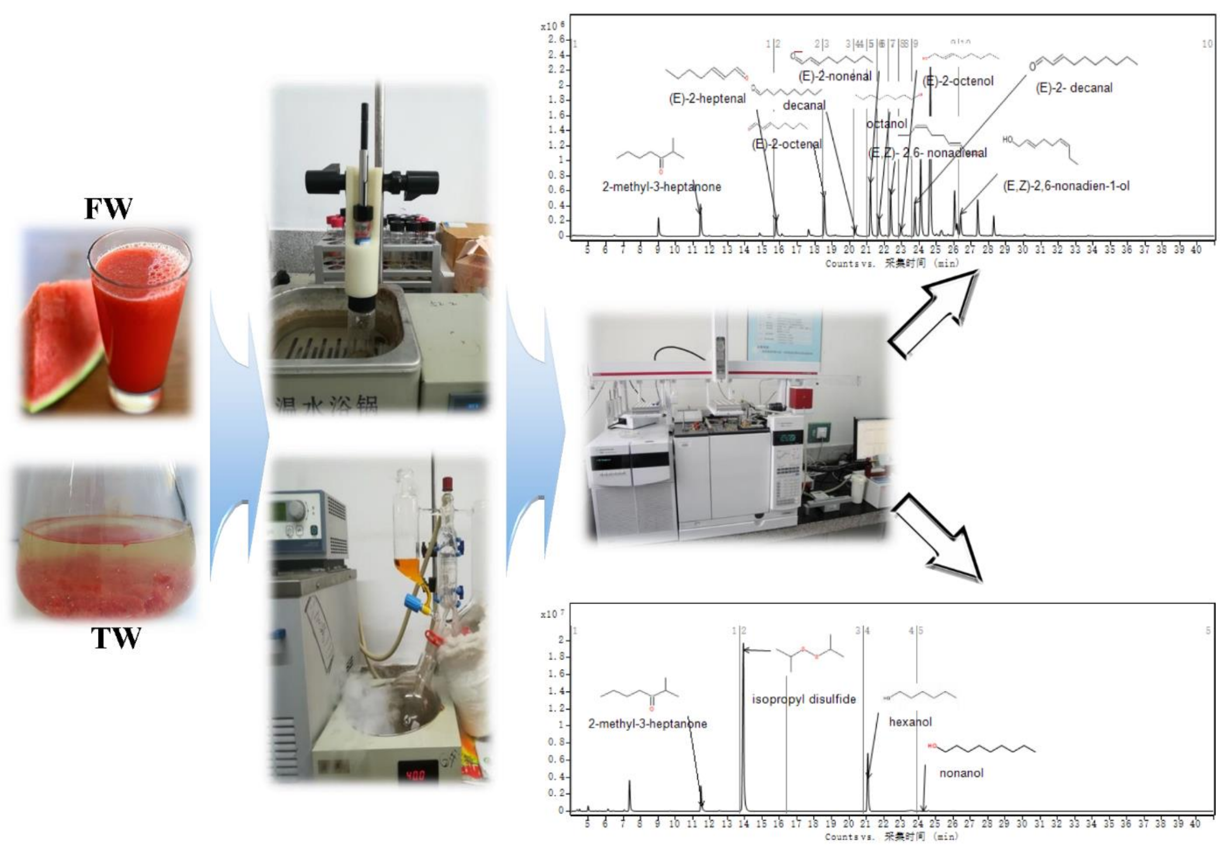


Figure 6 Identification of key off-flavor compounds in Thermally treated watermelon juice via Gas Chromatography Olfactory

1.6 Artificial Olfaction

The human nose has been used to evaluate perfume and food for a long time [1]. Smelling food is the best way to tell how fresh it is. Food that smells pleasant is new [2]. However, how do we smell? After smelling for a few hours, even the best inspector's nose can be a little off. And if we have a cold, what should we do? In situations like these, electronic noses are useful. Odors, vapors, and gases are recognized and automatically detected by an electronic nose. These are not restricted by human factors, for example, weakness, openness to poisons and powerlessness to identify come compounds [1]. Gas chromatography-mass spectrometry (GC/MS) and other expensive instruments for determining volatiles call for skilled personnel. Subsequently there has been a drive to lay out a gadget for fast, economical investigation of unpredictable natural mixtures (VOC) that don't need expert professionals. Persaud and Dodd first reported the design of an electronic nose (E-nose) using chemical sensors and pattern recognition in 1982. An e-nose is an instrument consisting of an array of reversible but only semi-selective gas sensors coupled to a pattern recognition algorithm. The selectivity of the instrument is achieved through the application of pattern recognition techniques to the responses from the senor array [3]. The possibility of using electronic nose for applications in indoor air quality monitoring, medical care, customs security, food quality control, environmental quality monitoring, military applications, and hazardous gas detection. has garnered increased research attention as of late. Several studies indicate that when people are afflicted with ailments such as diabetes, lung cancer, urinary tract infections, biological samples collected from them produce a discernable pattern of volatile organic compounds (VOCs) [1]. This forms, in essence, a “smell signature” for the disease that can be used to diagnose the condition with reasonable accuracy. In agriculture, fruits would generate different volatile organic compounds (VOCs) and concentration in different stages of maturity. However, the farmers still evaluate fruit maturity and quality by their experience; most of the time are not efficient and unscientific. Therefore, developing scientific method to real-time monitor fruit maturity & its quality has become an important topic in smart agriculture, for human health, transportation industry and food packaging industry. The electronic nose is not strictly used to prepare sensory characteristics of food products according to a definition it is a matter of sensory analysis with trained panelists. Therefore, it can be said that e-nose is an instrumental way to reveal some aroma discriminates of foods. An electronic nose is an instrument intended to mimic the human sense of smell. electronic noses are being used for analyses of the samples' aromatic profiles without prior separation of the volatile fraction into individual components. Electronic noses (e-nose) consist of an array of non- or partially selective gas sensors and are coupled with a data processing and pattern recognition system capable of identifying even complex aromatic profiles. Pattern recognition provides a higher degree of selectivity and reversibility to the system leading to an extensive range of applications. These ranges from the food and medical industries to environmental monitoring and process control. Various aromas affect different responses in the sensor system, and these reactions provide a signal pattern characteristic to a particular aroma [102]. The computer system recognizes the pattern of signals and then is able to compare the character of the aroma of varied foods' extracts by pattern recognition system, e.g., artificial neural network. This artificial olfaction could be helpful in the characterization of hundreds of samples in a relatively short time [103]. For instance, a producer who uses coffees from around the world can analyze coffee samples by e-nose, The analysis of numerous coffee samples, using the best conditions, can result in a group of points for each sample, that furthermore can be grouped. As the number of samples increases, the differences among the groups ought to also grow. Mapping the sensor responses of an unknown sample on the same scheme could allow its detection, by its proximity to one of the known samples.

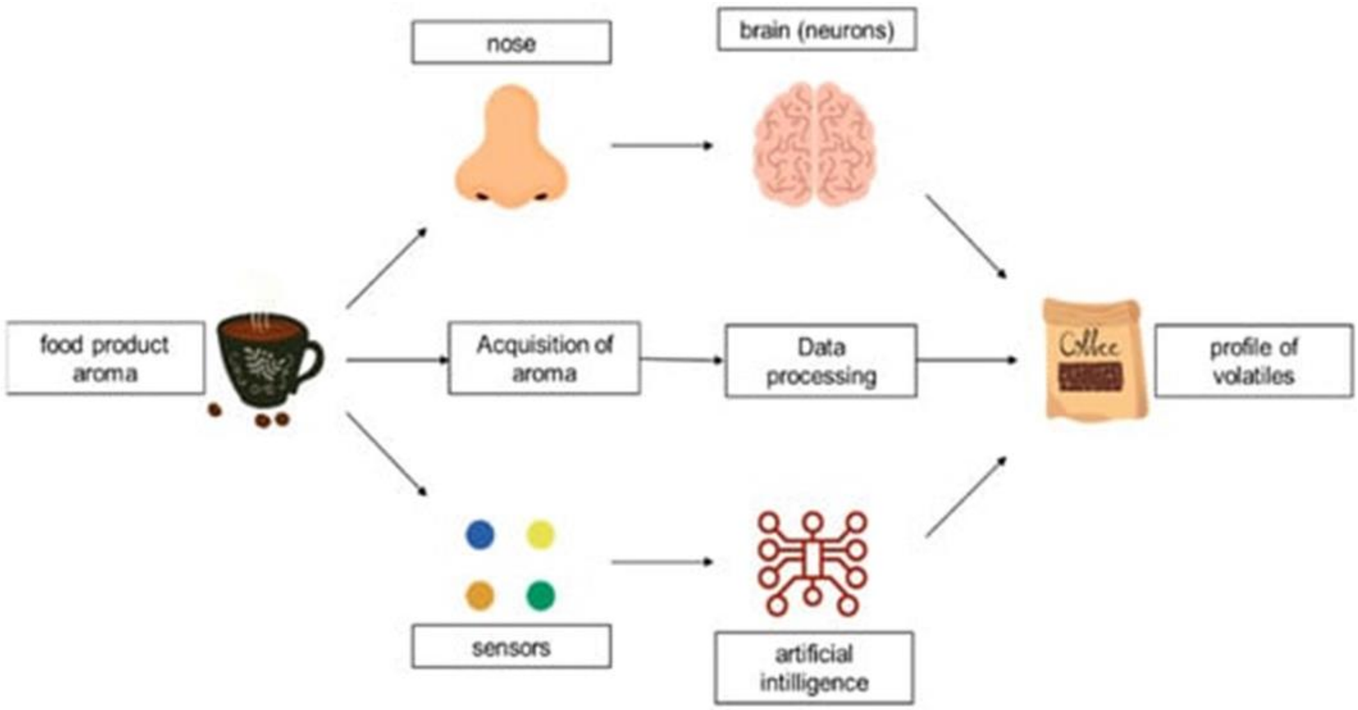


Figure 7 The Analogy between the biological olfactory system and enose technology

The use of this technique allows rapid non-destructive analysis and in certain applications can be an alternative to relatively costly and time-consuming techniques such as gas chromatography coupled with mass spectrometry (GC-MS) and/or olfactometry (GC-O), infrared spectroscopy (IR), and classical sensory analysis. The last one remains the standard in quality analysis partly because its results can be more directly related to the consumers' perception of the final product. However, sensory analysis is relatively costly as it requires the participation of trained panelists who can only work for several hours each day due to sensory fatigue [4]. It could be easily supplemented with electronic olfaction, in which also a holistic analysis of the sample's aromatic profile is performed. Food control is one of the main application areas of electronic noses, in particular in quality assessment and process operations in the food industry [5,6]. In fact, nearly half of the publications in the area of electronic olfaction are related to the food industry [7]. In the past, analytical devices equipped with arrays of sensors, such as electronic noses electronic tongues were developed for analyses of a large variety of food products, e.g., fish [7], meat [8], honey [9], coffee [10], cheese [11], spirits [12], or wine [13,14,15], and also more generic devices for general food analysis [16,17]. The latter ones have been developed into commercially available devices, as fewer specific solutions can be used in a wider area of applications, despite the fact that a more targeted approach might lead to a higher overall sensitivity and specificity of the system. In this report, a portable electronic nose intended for food analysis is presented. It is equipped with an array of MOS gas sensors mounted a breadboard, equipped with Arduino Uno as the microcontroller board. In order to adapt it to a particular application, individual sensor modules can be easily changed without the need to modify the platform in any way. Due to its portability, it can be used at all stages of the manufacturing process, whether during monitoring of production, quality evaluation during processing, or particularly at the retail level for freshness assessment.

The study of Lininger et al. [105] about the aroma of espresso coffee presented a higher correlation of sensory panel results with aroma characteristics obtained from online proton-transfer-reaction mass spectrometry (PTR-MS). The important innovation was using a combination of HS-SPME with a mass spectrometer detector and to determine the aroma of in-cup coffee [106]. The proposed method allows to receive the fingerprint of volatiles in tested food material and predict the sensory quality of other coffee beans; however, the limitations are a high number of samples that need to be analyzed to prepare a proper model and, in the next step, the insufficient access to data mining program. The basic electronic circuit for chemical identification using an array of sensors where each sensor is designed to respond to a specific chemical, the number of unique sensors must be at least as great as the number of chemicals begin monitored. The output characteristics of each sensor must be related with each other. The commercial Electronic Noses use sensors like conducting polymer sensors (CP), piezoelectric– surface acoustic wave (SAW), thickness shear mode (TSM), metal oxide semiconductor (MOS), metal oxide semiconductor field effect transistor (MOSFET), electrochemical (EC), Pallister and optical sensor arrays.

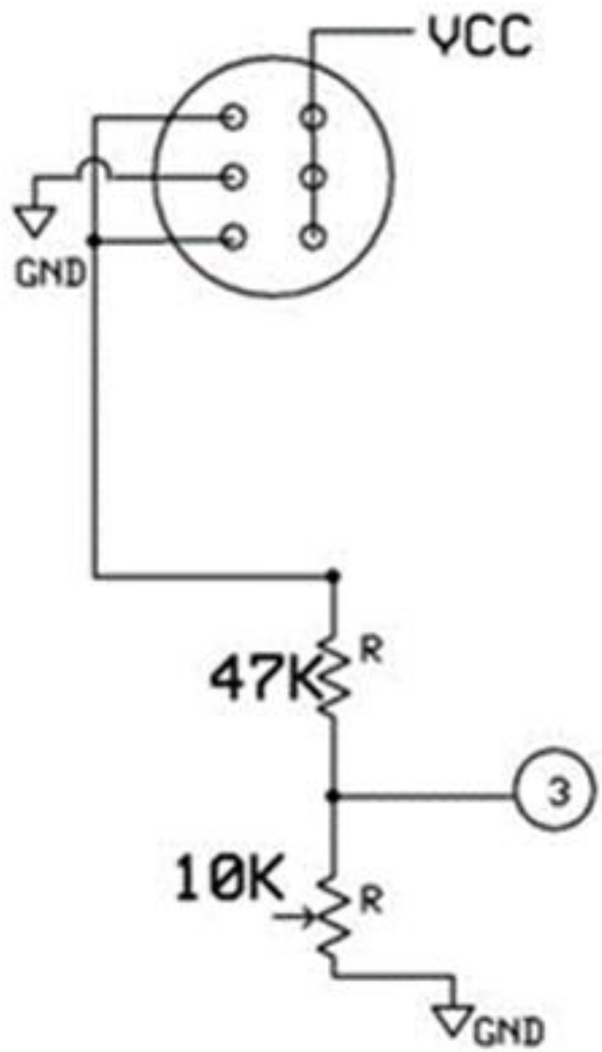


Figure 7 Internal Circuitry of MQ7 gas sensor

The sensing element of sensors is a tin oxide (SnO_2) semiconductor which has low conductivity in clean air. In the presence of a detectable gas, the sensor's conductivity increases depending on the concentration of gas in the air. A simple electrical circuit can convert the change in conductivity to an output signal which corresponds to the gas concentration. It makes detection by method of cycle high and low temperature, and detect CO as in case of MQ7 gas sensor when low temperature (heated by 1.5V). The sensor's conductivity is higher along with the gas concentration rising. The conducting polymer sensors used in electronic noses actually designed with thin films of insulating polymers loaded with carbon black as a conductive medium, to form polymer carbon composite. The polymers are selected by statistical analysis of responses of these films to a subset of the target compounds used. Since the resistance in most of the polymer- carbon composite films is sensitive to changes in temperature, heaters are included on back of the ceramic substrate to provide a constant temperature at the sensors. The application areas for electronic nose are growing on the basis of the results so far achieved on behalf of numerous research groups and more and more companies on the market. They are the following: Environmental control (air quality, pollutants, gas emission levels of factories, chemical plant monitoring etc.), Medical applications such as urine skin and breathe odor analysis, ulcer monitoring etc., Food industry (coffee, soft drinks, fish, meat, wine aroma control, fermentation process, identification of bacterial organism etc.) cosmetics/ perfumes and aroma, Defense and security industries (detecting humanitarian land mines etc.), Pharmaceutics, chemical industry (measuring odor, quality control of pharmaceutical compounds etc.), Semiconductor industrial process and others.

1.7 Sensors and Chemicals

The olfactory system can neither detect nor identify scents without the obtaining of chemicals released by the objects [23]. These chemicals can be found in simple or complex structures. Nevertheless, each individual chemical has its own unique quality and characteristics. Thus, digital signatures of chemicals, which are to be the input data for both the olfactory system and the EN instrument, are exclusive. The automatic detection process cannot be achieved without a collected library (dataset) of the digital signatures of specific aromas. The sensor array is responsible for detecting targeted chemicals in a medium. Each targeted aroma is detected with a specific sensor, in other words each individual sensor is responsible for sensing a specific type of aroma. Chemical sensors are used for detecting chemicals in the medium. These sensors basically convert chemical information into analytical signals [24]. Since the main objective of an EN is to sense more than one chemical, this aim can be achieved with higher accuracy only by combining several distinct sensors in the array. While keeping in mind that the sensors in the array have to be chosen carefully by taking the chemicals of interest into account [25], having a proper sensor array for specific tasks depends on several conditions as follows [26]:

- small size and easy to use
- re-usability and inexpensiveness
- short response time and regeneration time
- high resistance for different mediums
- insensitivity to temperature and humidity
- high sensitivity and selectivity with respect to chemical compounds or substance including in the gas mixtures;

- high stability for the selected application.

There are numerous numbers of sensor types utilized in the EN technology. The report has summarized below the most commonly used ones which have been applied in various practical applications and their properties including advantages and disadvantages shown in the table below:

Table 1 Sensor types and their properties

Sensor type	Detection range	Usage area	Advantages	Disadvantages
Metal oxide	5–500ppm	Food and beverage industry Indoor and outdoor monitoring	Suitable to range of gases Operation in high temperature High power consumption Fast response, small size, easy to use	High sensitivity and specificity Sulphur poisoning Weak precision Humidity sensitive
Conducting polymer	0.1–100ppm	Medical industry Pharmaceutical industry Food and beverage industry Environmental monitoring	Sensitive to range of gases Fast response and low cost Resistant to sensor poisoning Use at room temperature	Humidity sensitive Temperature sensitive Limited sensor life Affected from drift
Quartz crystal microbalance	1.5Hz/ppm 1ng mass change	Pharmaceutical industry Environmental monitoring Food industry Security systems	Good sensitivity Low detection limits Fast response	Hard to implement Poor signal-to-noise ratio Humidity sensitive Temperature sensitive
Acoustic wave	100–400MHz	Environmental monitoring Food and beverage industry Chemical detection Automotive industry	Small size and low cost Good sensitivity and response time Response to nearly all gases	Hard to implement Temperature sensitive Poor signal-to-noise ratio
Electro-chemical	0–1000ppm adjustable	Security systems Industrial applications Medical applications	Power efficient and robust High range operation temperature Sensitive to diverse gases	Large size Limited sensitivity
Catalytic bead	Large scale	Environmental monitoring Chemical monitoring	Fast response High specificity for combustible gases	Operate in high temperature Only for compounds with oxygen
Optical	Change with… light parameters low ppb	Biomedical applications Environmental monitoring	Low cost and light weight Immune to electromagnetic interference Rapid and very high sensitivity	Hard to implement Low portability Affected by light interference

Metal-Oxide Sensors

MOS is the most commonly used sensor type in the EN instrument because of its suitability for wide range of gases [27]. The practical application areas of MOS based ENs are mainly related to quality control, monitoring, process, aging, geographical origin, adulteration, contamination and spoilage of food and beverages [28]. These sensors can operate at high temperatures but require high power consumption. On the other hand, oxide surface reactions are too slow at lower temperatures. The oxidative chemical reactions are constrained due to the low vapor pressure of water molecules at temperatures below 100 °C [29]. MOS are categorized into two main groups according to their responses to different gases [19]: 1) n-type and 2) p-type. The operational principle of n-type sensors is based on the reactions between the oxygen molecules in the air and the surface of these sensors. As a result of these reactions, free electrons on the surface are trapped resulting in potential barriers between grains which inhibit the carrier mobility that produces large resistance areas. The p-type sensors respond to oxidizing gases, remove electrons and produce holes. Their characteristic surface reactivity and oxygen absorption significantly increase the performance of the sensor, while enhancing the recovery speed, boosting the gas selectivity and reducing the humidity dependence of signals. These sensors are frequently chosen in many EN applications because of their high sensitivity and selectivity.

Figure 8 MOS gas sensor of MQ family

Conducting polymer sensors

Although there are some drawbacks such as the inability of detecting gases like trimethylamine in fish odor applications, conducting polymers are a reliable sensor type used in many EN instruments for medical, pharmaceutical, food and beverage industries, because of their low cost, fast response to odorants and resistance to sensor poisoning [19]. Since the active layers are crucial parts of sensors, there are many different manufacturing processes of conducting polymer films including vapor deposition polymerization, thermal evaporation, electrochemical deposition, layer-by-layer (Lbl) self-assembly technique, well-known Langmuir-Blodgett (LB) technique and more [31].

Several conducting polymers are used in sensors such as polypyrene, polyaniline and polythiophene [31]. When a change occurs in the material due to an interaction with an analyte, the resistance in the sensor changes which leads to the detection of gases.

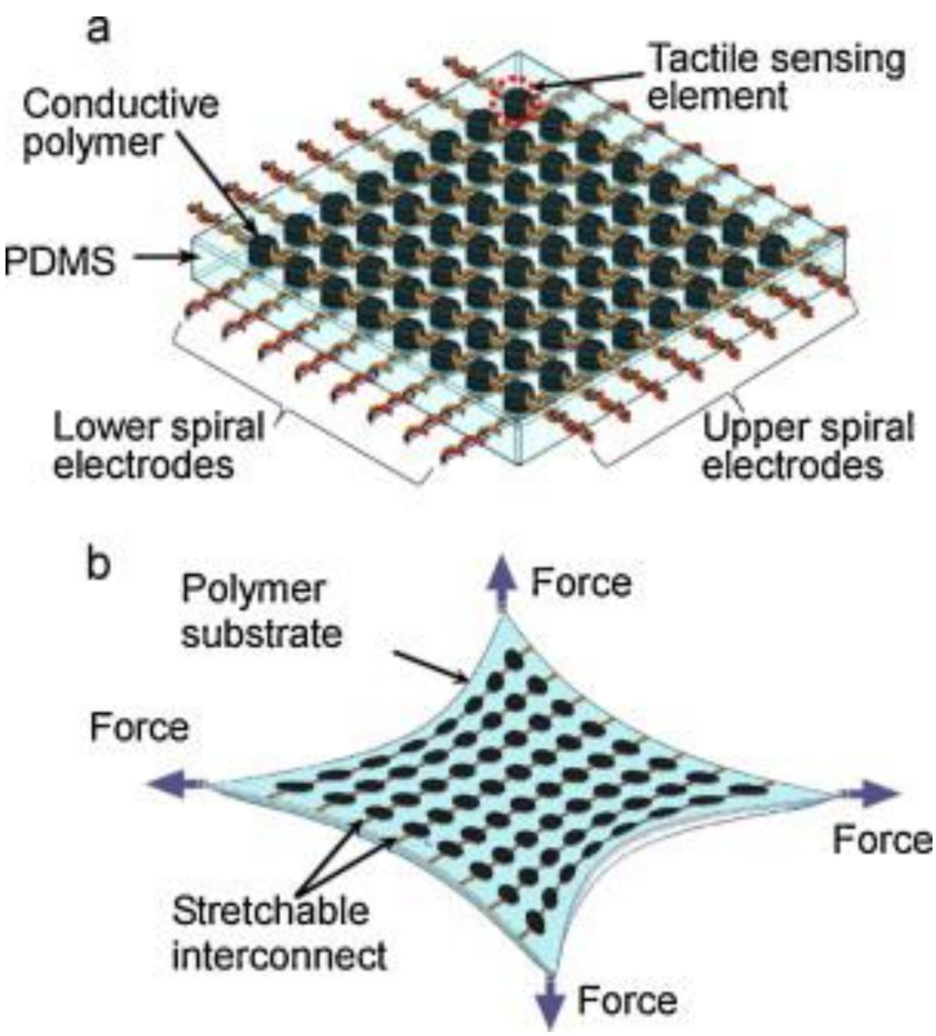


Figure 9 Conducting Polymer Sensor

Quartz crystal microbalance (QCM) sensors

QCM sensors are chosen as an EN component in several applications including medicine, environment monitoring, security and food safety because of their sensitivity, convenience, rapidness, stability and portability. In these sensors, the surfaces are covered with a sensitive coating [19]. A selective barrier on the crystal surface takes in the released gas from the environment, which then increases the total mass. Subsequently, frequency decreases because of the mass change on the gold surface of the QCM. Therefore, QCM sensors determine small variations on the sensor surface by measuring the frequency changes on the quartz crystal resonator. QCM sensors can operate in gas and liquid environments to determine the properties of chemicals [33]. Along with sensitive biosensors, they can detect even a nanogram of substance [34]. Importantly, QCM sensors are open for changes and improvements. The surface of these sensors can be modified so that they can detect entire cells or only one single molecular monolayer. Sensor enhancements can be actualized by an electrochemical approach, via immobilization of the silver electrode surface polyaniline film [35]. Furthermore, the biotoxicity of metallic electrodes caused by some bioactive coating films can be eliminated through employing electrodeless crystal configurations [36]. Additionally, molecularly imprinted polymers (MIPs)[37], polished gold films[38], biomimetic peptide-based sensing materials[39], multi-wall carbon nanotubes [40], acidized-multiwalled carbon nanotubes [41] and calixarenes [42] can be used in QCM sensors to coat surface layers. QCM based biosensors are commonly adopted to analyze odors because of their economic and easy manufacturing, and rapid analysis ability.

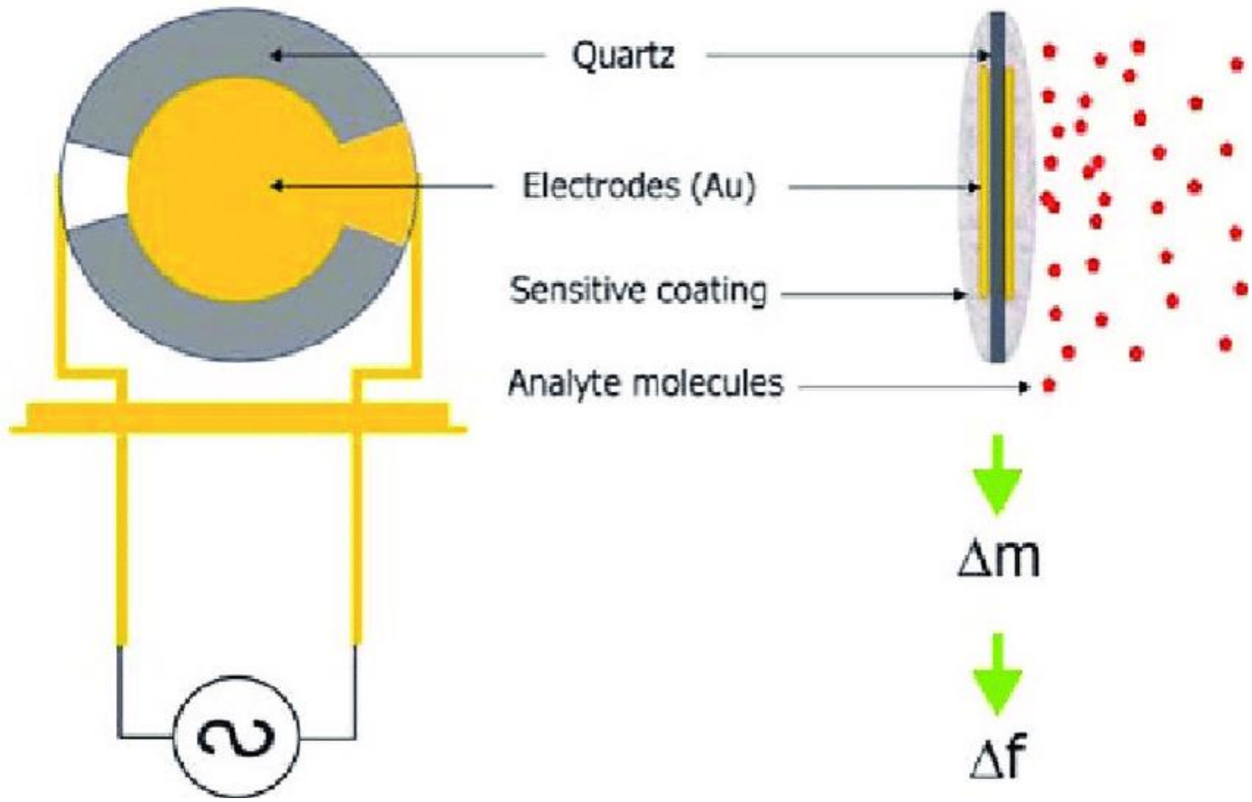


Figure 10 Quartz Crystal Microbalance Gas Sensor Working Principle

Acoustic wave sensors

The first study about these sensors was in [44]. There are several acoustic wave sensor types, such as flexural plate wave device, fiber acoustic wave sensor, tube acoustic wave device, transverse wave device, bulk acoustic wave (BAW) and surface acoustic wave (SAW) sensors. BAW and SAW are frequently utilized in EN applications because of their small size, sensitivity, low cost and response to nearly all gases [45]. BAW sensors operate in the same way as QCM sensors, but they are less sensitive. They can measure extremely small frequency changes by means of their stability. Low cost, simplicity and robustness are other advantages of BAW sensors. However, the performance of these sensors in a liquid medium is inadequate. SAW sensors are derived from

BAW devices. High sensitivity is achieved by operating at high frequencies. However, the signal-to-noise performance is poor in SAW sensors because of the high operating frequencies.

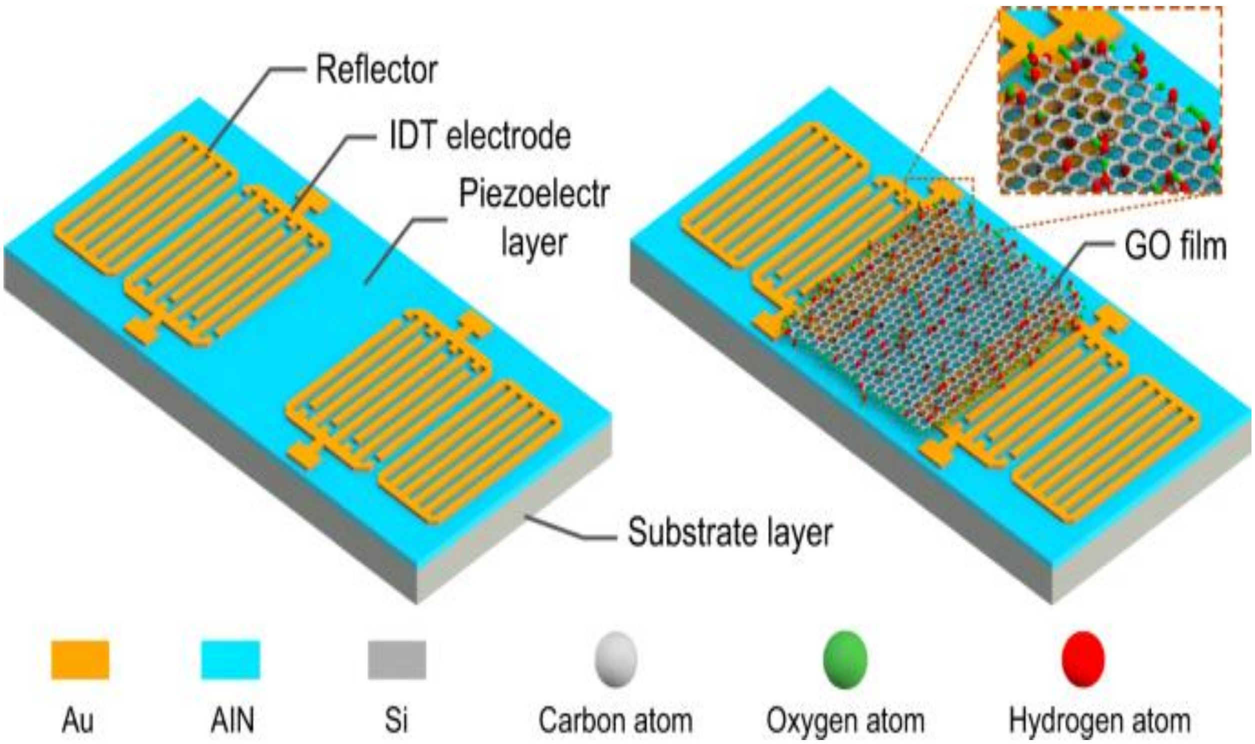


Figure 11 Acoustic Wave Sensor

Electrochemical (EC) gas sensors

Electrochemical (EC) gas sensors are devices that use chemical reactions to detect and measure the concentration of various gases in the environment. These sensors work by converting the gas molecules into an electric current, which can then be measured and analyzed. EC gas sensors typically consist of two electrodes separated by an electrolyte. One electrode is coated with a material that reacts with the gas being detected, while the other electrode remains inert. When the gas comes into contact with the reactive electrode, a chemical reaction occurs, which generates an electric current. The magnitude of the current is directly proportional to the concentration of the gas being detected. EC gas sensors are widely used in industrial, commercial, and residential settings to monitor and control the levels of toxic or flammable gases, such as carbon monoxide, methane, and hydrogen sulfide. They are also used in medical applications, such as monitoring the concentration of gases in the breath of patients. EC gas sensors offer several advantages over other types of gas sensors, including high sensitivity, accuracy, and selectivity. They are also relatively inexpensive, easy to use, and require minimal maintenance. However, they do have some limitations, such as a limited lifespan and susceptibility to interference from other gases and environmental factors.

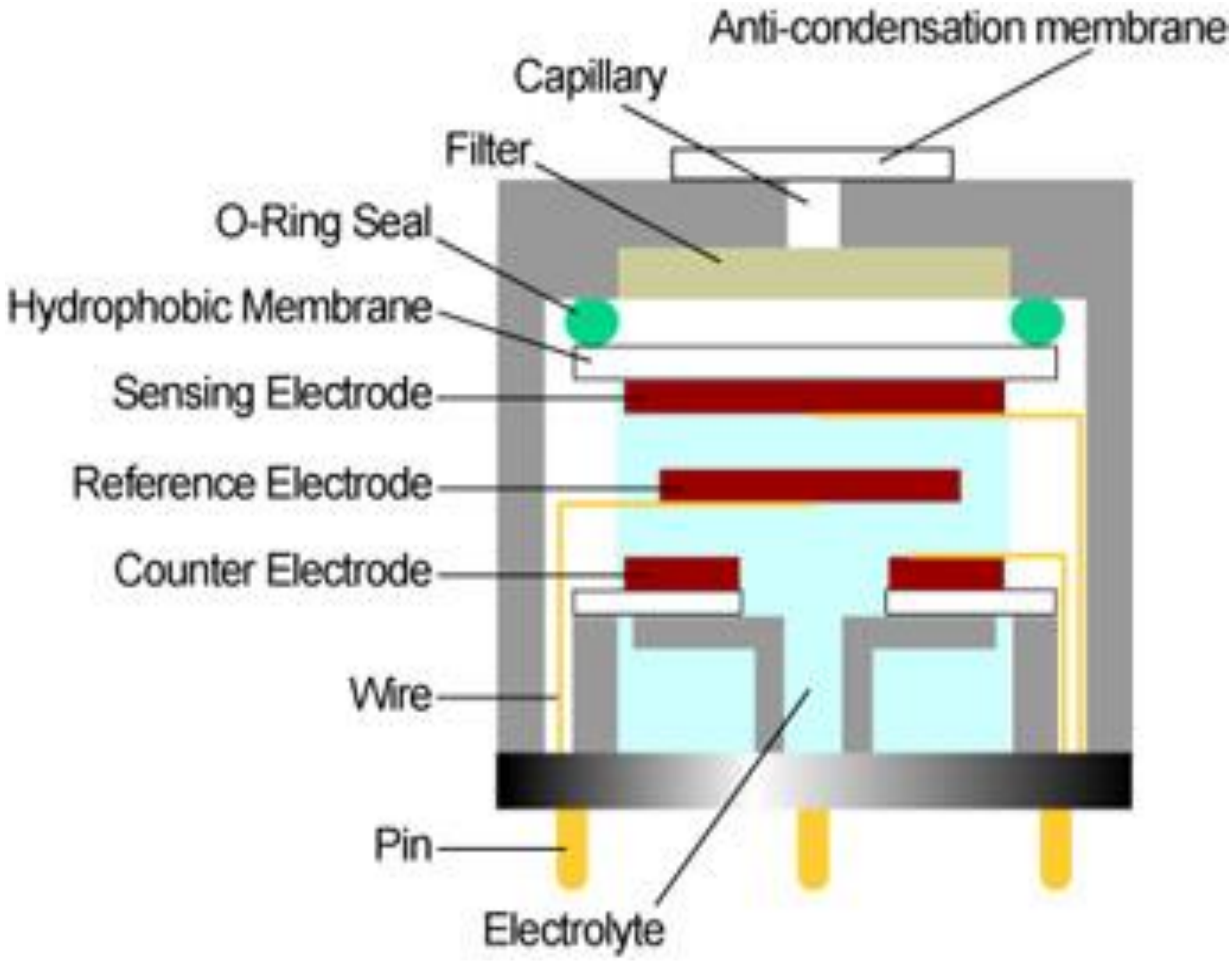


Figure 12 Electro Chemical Gas Sensor

Catalytic bead (CB) sensors

Catalytic bead sensors are a type of gas sensor that are commonly used to detect the presence of combustible gases such as methane, propane, and hydrogen in industrial and domestic settings. The sensors consist of two small platinum wires coated with a catalyst such as palladium or platinum. When combustible gas is present, it reacts with the catalyst on the surface of the wires, causing the wires to heat up and increase in resistance. This change in resistance is then measured and used to determine the concentration of the gas in the surrounding environment. Catalytic bead sensors are highly sensitive and can detect combustible gases at very low concentrations, making them ideal for use in environments where gas leaks could be dangerous. They are also relatively inexpensive and easy to use, which has made them popular in a range of industries including oil and gas, chemical manufacturing, and mining. However, catalytic bead sensors are not suitable for use in environments where there are high levels of oxygen or other oxidizing gases present, as these can cause the wires to overheat and become damaged. Additionally, they are not effective at detecting non-combustible gases such as carbon dioxide or nitrogen.

Figure 13 Catalytic Bead Sensor

Optical sensors

Optical sensors are attractive for use in several EN applications, e.g., [48], because of their compactness, immunity to electromagnetic interference and rapidity [19]. Fluorescence, optical layer thickness, colorimetric dye response, light polarization and absorbance are measured by optical sensors, and any of these optical changes are used to detect odors in the environment [7]. There are two special types of optical sensors, which detect subjects based on the differences of color, i.e., colorimetric sensors, and light, i.e., fluorescence sensors. Colorimetric sensors are composed of thin films made of chemically responsive dyes. Fluorescence sensors which are more sensitive than colorimetric sensors, identify fluorescent light emissions released by samples.

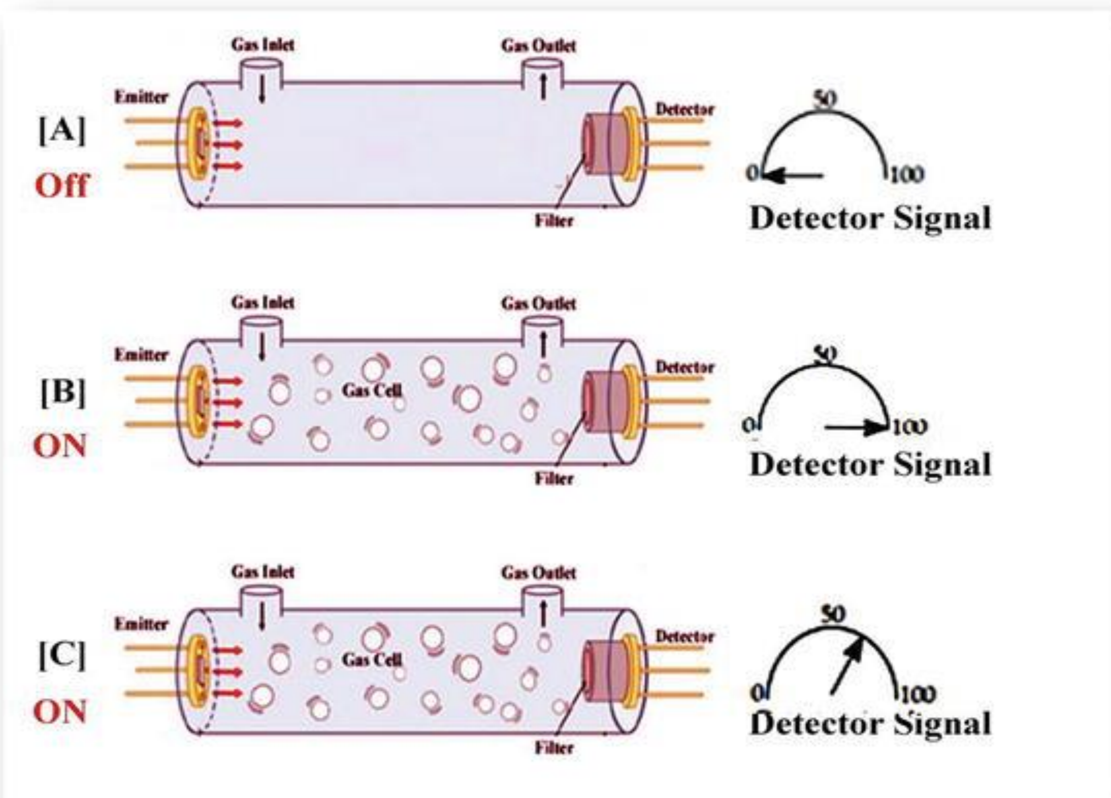


Figure 14 Optical Gas Sensor

Photoionization detector (PID) sensors

A photoionization detector (PID) is a type of gas sensor that detects volatile organic compounds (VOCs) in the air by ionizing the gas molecules using ultraviolet (UV) light. The PID is commonly used in industrial and environmental applications, such as detecting hazardous gases in factories, monitoring air quality in cities, and testing for leaks in underground storage tanks. The PID works by emitting UV light onto the gas sample, which ionizes the gas molecules and produces positively charged ions and free electrons. The positively charged ions are attracted to the negatively charged electrode, while the free electrons are attracted to the positively charged electrode. The resulting electrical current is proportional to the concentration of the VOCs in the gas sample. One advantage of the PID is its high sensitivity to low levels of VOCs. The device is also fast and easy to use, requiring no preparation or calibration. However, the PID can only detect certain types of gases and can be affected by humidity, temperature, and other environmental factors. It is important to select the appropriate PID sensor for the specific gas being detected and to ensure proper maintenance and calibration of the device. By using the ultraviolet light, via high energy photons, the molecules of the targeted gas start to ionize. As a result of this ionization, formed ions create an electric current which can be detected by PID sensors at different concentration levels (parts per million (ppm) or parts per billion (ppb))[49]. Although the photo-ionization detector (PID) and quadrupole fingerprint mass spectrometers (QFMS) are not considered ENs in the strictest sense because they do not provide a collective data output from a sensor array and are designed to detect and identify individual components of a gas mixture, the PID type sensors are able to detect individual compounds and are currently used in the EN systems.

Figure 15 Photoionization Detector

1.8 CHAPTER

Proposed Model

E-Nose System Procedure

The e-nose system comprises of (1) the sensing mechanism that will generate the sensor resistance values depending on the gases it will detect and (2) the Arduino Uno the main microcontroller board, that would transform the gas sensor array functional & store the analog values to a data acquisition card. The data obtained is fed to sophisticated machine learning algorithms for classifying these data using Linear SVM & Random Forest algorithm. The output classification plots obtained has to be compared so as to have an in-depth understanding of the dataset itself thereby clarifying the effectiveness of each of the machine learning models applied, for the sake of accuracy. The input comes from the banana sample which has been used as the target element. The gases emitted from the samples is sensed by the array of sensors made up of MQ sensors; (Alcohol and Carbon Monoxide) a series of gas-sensitive sensors that detects volatile compounds concentrations. The concentration of the gases sensed from the three stages of the fruit ripening – fresh & ripened generate a collective response that is sent to the Arduino Uno analog input ports. The collected data from the sensors array will be used to feed the SVM Algorithm. Support vector machines are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis, is used for analyzing a collective response such as gas ppm levels, so as to classify the fresh from the spoiled and semi-spoiled.

Components of Electronic Nose System

- **Arduino Uno**

The Arduino Uno is an open-source microcontroller board based on the Microchip ATmega328P microcontroller and developed by Arduino.cc and initially released in 2010.[2][3] The board is equipped with sets of digital and analog input/output (I/O) pins that may be interfaced to various expansion boards (shields) and other circuits.[1] The board has 14 digital I/O pins (six capable of PWM output), 6 analog I/O pins, and is programmable with the Arduino IDE (Integrated Development Environment), via a type B USB cable.[4] It can be powered by a USB cable or a barrel connector that accepts voltages between 7 and 20 volts, such as a rectangular 9-volt battery. It is similar to the Arduino Nano and Leonardo.[5][6] The hardware reference design is distributed under a Creative Commons Attribution Share-Alike 2.5 license and is available on the Arduino website. Layout and production files for some versions of the hardware are also available. The word "uno" means "one" in Italian and was chosen to mark a major redesign of the Arduino hardware and software.[7] The Uno board was the successor of the Duemilanove release and was the 9th version in a series of USB-based Arduino boards.[8] Version 1.0 of the Arduino IDE for the Arduino Uno board has now evolved to newer releases.[4] The ATmega328 on the board comes preprogrammed with a bootloader that allows uploading new code to it without the use of an external hardware programmer.[3]While the Uno communicates using the original STK500 protocol,[1] it differs from all preceding boards in that it does not use a FTDI USB-to-UART serial chip. Instead, it uses the Atmega16U2 (Atmega8U2 up to version R2) programmed as a USB-to-serial converter.

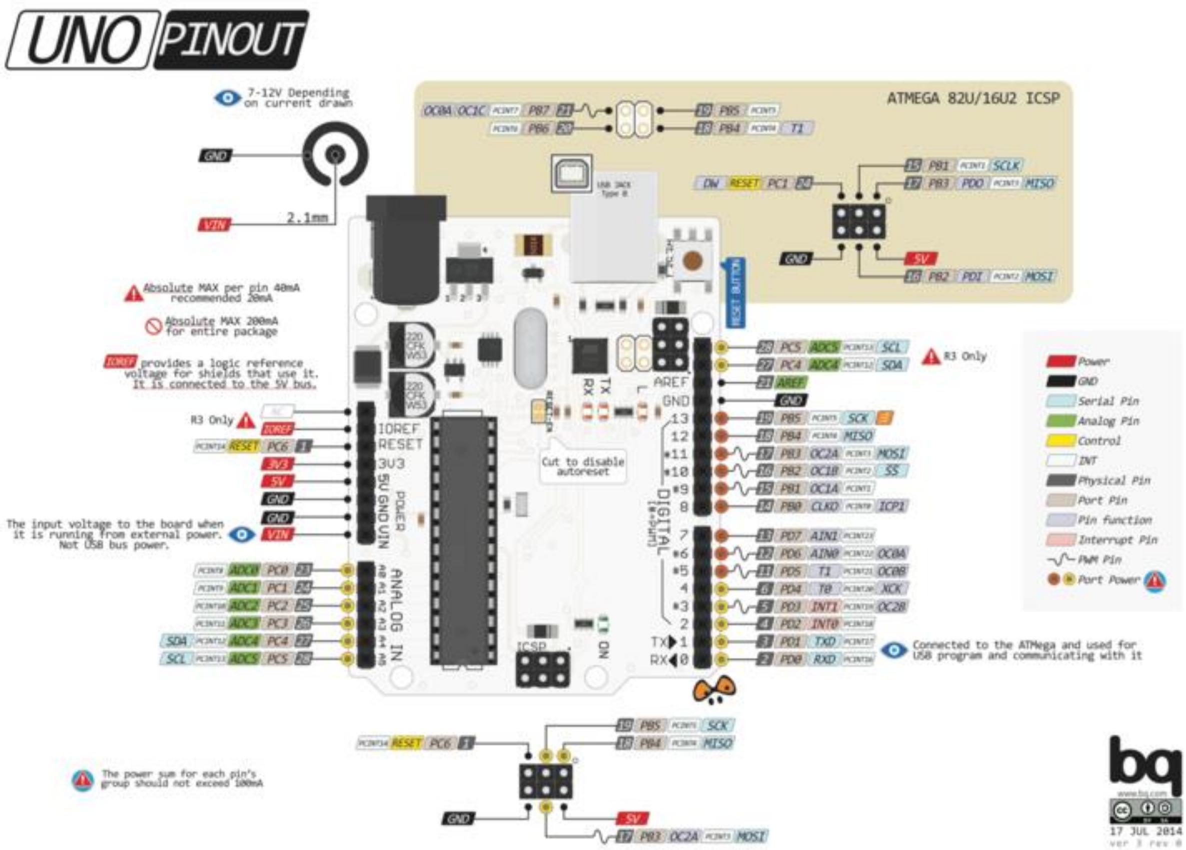


Figure 16 Arduino Uno Pin Out Functions

Each of the 14 digital pins and 6 analog pins on the Uno can be used as an input or output, under software control (using pin Mode (), digital Write (), and digital Read () functions). They operate at 5 volts. Each pin can provide or receive 20 mA as the recommended operating condition and has an internal pull-up resistor (disconnected by default) of 20-50K ohm. A maximum of 40mA must not be exceeded on any I/O pin to avoid permanent damage to the microcontroller. The Uno has 6 analog inputs, labeled A0 through A5; each provides 10 bits of resolution (i.e., 1024 different values). By default, they measure from ground to 5 volts, though it is possible to change the upper end of the range using the AREF pin and the analog Reference() function.[9]In addition, some pins have specialized functions:

- Serial / UART: pins 0 (RX) and 1 (TX). Used to receive (RX) and transmit (TX) TTL serial data. These pins are connected to the corresponding pins of the ATmega8U2 USB-to-TTL serial chip.
- External interrupts: pins 2 and 3. These pins can be configured to trigger an interrupt on a low value, a rising or falling edge, or a change in value.
- PWM (pulse-width modulation): pins 3, 5, 6, 9, 10, and 11. Can provide 8-bit PWM output with the analog Write () function.
- SPI (Serial Peripheral Interface): pins 10 (SS), 11 (MOSI), 12 (MISO), and 13 (SCK). These pins support SPI communication using the SPI library.
- TWI (two-wire interface) / I²C: pin SDA (A4) and pin SCL (A5). Support TWI communication using the Wire library.
- AREF (analog reference): Reference voltage for the analog inputs.

The Arduino/Genuine Uno has a number of facilities for communicating with a computer, another Arduino/Genuine board, or other microcontrollers. The ATmega328 provides UART TTL (5V) serial communication, which is available on digital pins 0 (RX) and 1 (TX). An ATmega16U2 on the board channels this serial communication over USB and appears as a virtual com port to software on the computer. The 16U2 firmware uses the standard USB COM drivers, and no external driver is needed. However, on Windows, a .inf file is required. Arduino Software (IDE) includes a serial monitor which allows simple textual data to be sent to and from the board. The RX and TX LEDs on the board will flash when data is being transmitted via the USB-to-serial chip and USB connection to the computer (but not for serial communication on pins 0 and 1). A Software Serial library allows serial communication on any of the Uno's digital pins.

- **MQ3 Gas Sensor**

MQ-3 module is suitable for detecting Alcohol, Benzine, CH_4, Hexane, LPG, CO. Sensitive material of MQ-3 gas sensor is SnO_2, which with lower conductivity in clean air. When the target alcohol gas exists, the sensor's conductivity is higher along with the gas concentration rising. MQ-3 gas sensor has high sensitivity to Alcohol, and has good resistance to disturb of gasoline, smoke and vapor. This sensor provides an analog resistive output based on alcohol concentration. When the alcohol gas exists, the sensor's conductivity gets higher along with the gas concentration rising. There is a resistance across an A and B inside the sensor which varies on detection of alcohol. More the alcohol, the lower the resistance. The alcohol is measured by measuring this resistance. The sensor and load resistor form a voltage divider, and the lower the sensor resistance, the higher the voltage reading will be.

Features of MQ3:

- High sensitivity to alcohol and small sensitivity to Benzine.
- Fast response and High sensitivity
- Stable and long life
- Simple drive circuit

SPECIFICATIONS

A. Standard work condition

Symbol	Parameter name	Technical condition	Remarks
Vc	Circuit voltage	5V±0.1	AC OR DC
V_H	Heating voltage	5V±0.1	ACOR DC
R_L	Load resistance	200K Ω	
R_H	Heater resistance	33 Ω ±5%	Room Tem
P_H	Heating consumption	less than 750mw	

B. Environment condition

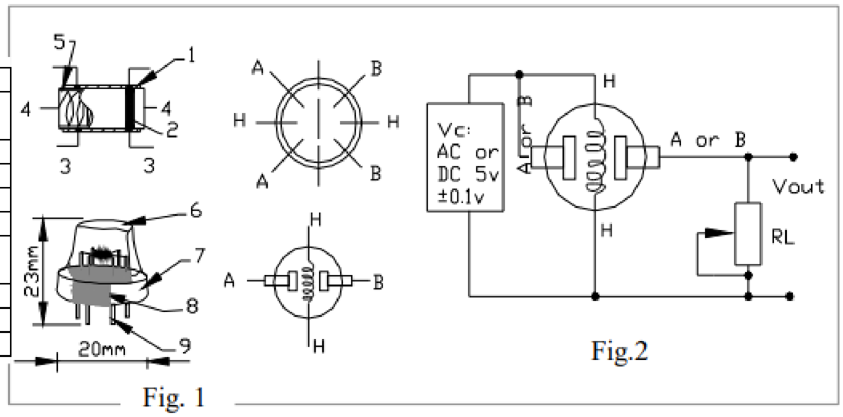
Symbol	Parameter name	Technical condition	Remarks
Tao	Using Tem	-10℃-50℃	
Tas	Storage Tem	-20℃-70℃	
R_H	Related humidity	less than 95%Rh	
O_2	Oxygen concentration	21%(standard condition)Oxygen concentration can affect sensitivity	minimum value is over 2%

C. Sensitivity characteristic

Symbol	Parameter name	Technical parameter	Remarks
Rs	Sensing Resistance	1M Ω - 8 M Ω (0.4mg/L alcohol)	Detecting concentration scope: 0.05mg/L—10mg/L Alcohol
α (0.4/1 mg/L)	Concentration slope rate	≤0.6	
Standard detecting condition	Temp: 20℃ ±2℃ Vc:5V±0.1 Humidity: 65%±5% Vh: 5V±0.1		
Preheat time	Over 24 hour		

Structure and configuration of MQ-3 gas sensor is shown in the figure below (Configuation A or B), sensor composed by micro AL2O3 ceramic tube, Tin Dioxide (SnO2) sensitive layer, measuring electrode and heater are fixed into a crust made by plastic and stainless-steel net. The heater provides necessary work conditions for work of sensitive components. The enveloped MQ3 have 6 pins ,4 of them is used to fetch signals, and other 2 are used for providing heating current.

	Parts	Materials
1	Gas sensing layer	SnO_2
2	Electrode	Au
3	Electrode line	Pt
4	Heater coil	Ni-Cr alloy
5	Tubular ceramic	Al_2O_3
6	Anti-explosion network	Stainless steel gauze (SUS316 100-mesh)
7	Clamp ring	Copper plating Ni
8	Resin base	Bakelite
9	Tube Pin	Copper plating Ni



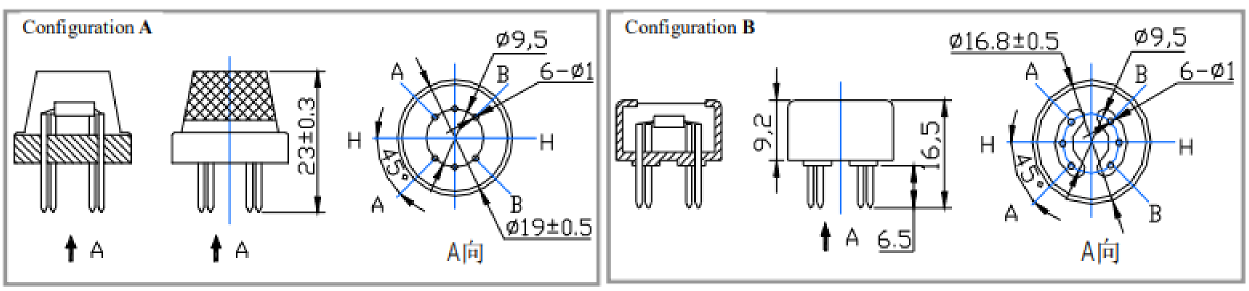


Figure 17 Structure & Configuration, Basic Measuring Circuitry

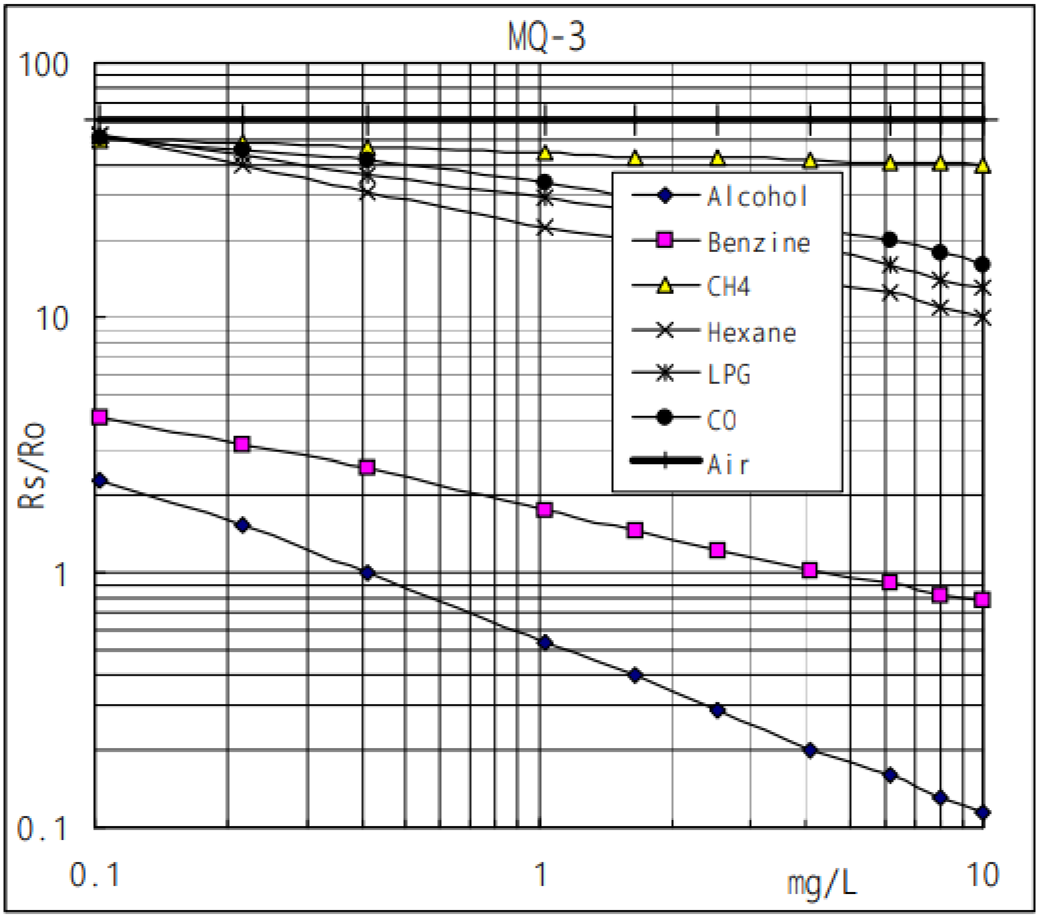


Figure 18 Sensitivity Characteristics of MQ3

Resistance value of MQ-3 is difference to various kinds and various concentration gases. So, when using this component, sensitivity adjustment is very necessary. we recommend that you calibrate the detector for 0.4mg/L (approximately 200ppm) of Alcohol concentration in air and use value of Load resistance that (RL) about 200 KΩ (100KΩ to 470 KΩ).

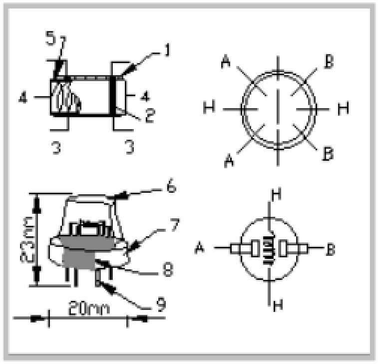
- **MQ7 Gas Sensor**

MQ7 Gas sensor is another one of Metal Oxide Semiconductor (MOS) type Gas Sensor of MQ Gas Sensors family involving MQ 2, MQ 4, MQ 3, MQ 8, MQ 135, etc. It is mainly used to detect Carbon Monoxide. This sensor contains a sensing element, mainly aluminum-oxide based ceramic, coated with Tin dioxide (SnO_2), enclosed in a stainless-steel mesh. Whenever CO gas comes into contact with the sensing element, the resistivity of the element changes. The change is then measured to get the concentration of the gases present. The MQ7 Sensor has a small heating element present which is needed to preheat the sensor to get it in the working window. It can detect Carbon Monoxide Gas in the range of 20 PPM to 2000 PPM in the air. It finds uses in Alarm application in case of CO gas concentration build-up in the home or your car as CO is a very harmful gas and can kill a person if present over 300PPM.

Features of MQ3:

- High sensitivity to carbon monoxide
- Stable and long life

Structure and configuration of MQ-7 gas sensor is shown in the figure below (Configuration A or B), sensor composed by micro AL_2O_3 ceramic tube, Tin Dioxide (SnO_2) sensitive layer, measuring electrode and heater are fixed into a crust made by plastic and stainless-steel net. The heater provides necessary work conditions for work of sensitive components. The enveloped MQ-7 have 6 pins ,4 of them is used to fetch signals, and other 2 are used for providing heating current.



	Parts	Materials
1	Gas sensing layer	SnO_2
2	Electrode	Au
3	Electrode line	Pt
4	Heater coil	Ni-Cr alloy
5	Tubular ceramic	Al_2O_3
6	Anti-explosion network	Stainless steel gauze (SUS316 100-mesh)
7	Clamp ring	Copper plating Ni
8	Resin base	Bakelite
9	Tube Pin	Copper plating Ni

Fig.1

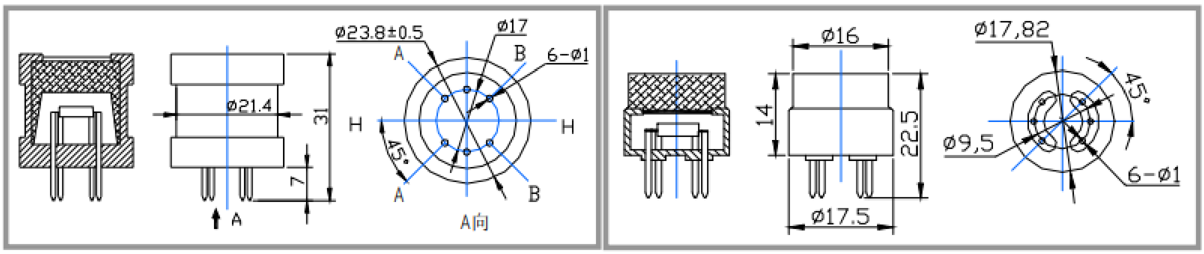


Figure 19 Structure & Configuration of MQ7

The surface resistance of the sensor Rs is obtained through effected voltage signal output of the load resistance RL which series-wound. The relationship between them is described:

$$Rs\backslash RL = (Vc\text{-}VRL) / VRL$$

Sensitive layer of MQ-7 gas sensitive components is made of SnO2 with stability, So, it has excellent long-term stability. Its service life can reach 5 years under using condition.

SPECIFICATIONS

A. Standard work condition

Symbol	Parameter name	Technical condition	Remark
Vc	circuit voltage	5V±0.1	Ac or Dc
V_H (H)	Heating voltage (high)	5V±0.1	Ac or Dc
V_H (L)	Heating voltage (low)	1.4V±0.1	Ac or Dc
R_L	Load resistance	Can adjust	
R_H	Heating resistance	33Ω±5%	Room temperature
$T_{H\,(H)}$	Heating time (high)	60±1 seconds	
$T_{H\,(L)}$	Heating time (low)	90±1 seconds	
PH	Heating consumption	About 350mW	

b. Environment conditions

Symbol	Parameters	Technical conditions	Remark
Tao	Using temperature	-20℃-50℃	
Tas	Storage temperature	-20℃-50℃	Advice using scope
RH	Relative humidity	Less than 95%RH	
O_2	Oxygen concentration	21%(stand condition) the oxygen concentration can affect the sensitivity characteristic	Minimum value is over 2%

c. Sensitivity characteristic

symbol	Parameters	Technical parameters	Remark
Rs	Surface resistance Of sensitive body	2-20k	In 100ppm Carbon Monoxide
a (300/100ppm)	Concentration slope rate	Less than 0.5	Rs (300ppm)/Rs(100ppm)
Standard working condition	Temperature -20℃±2℃ relative humidity 65%±5% RL:10KΩ±5%		
	Vc:5V±0.1V VH:5V±0.1V VH:1.4V±0.1V		
Preheat time	No less than 48 hours	Detecting range: 20ppm-2000ppm carbon monoxide	

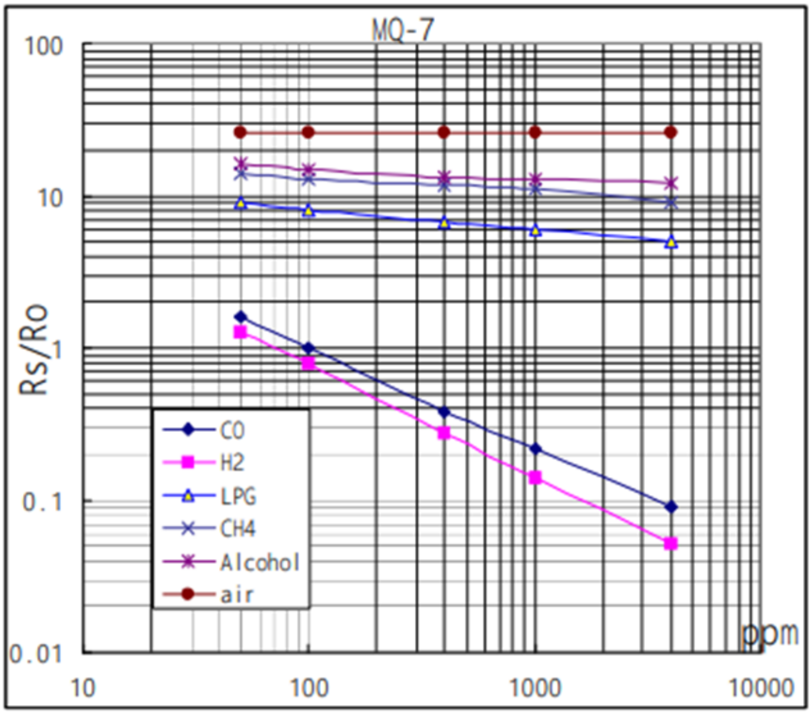


Fig.3 sensitivity characteristics of the MQ-7

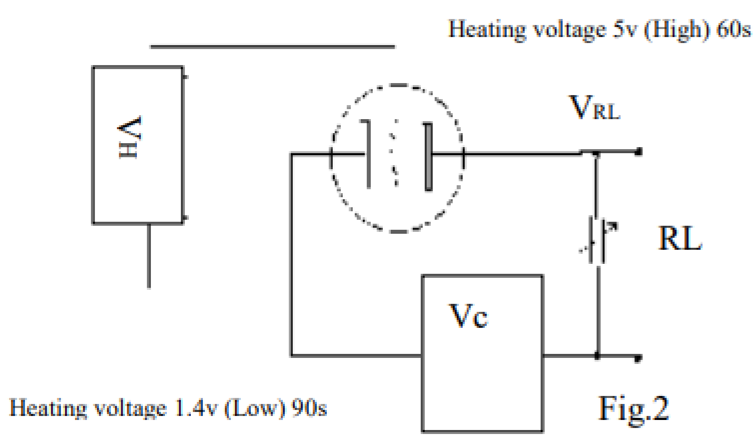


Figure 20 Standard Circuitry of MQ7

Software Development

Lifeline of Sensor Array

The Arduino IDE is a cross-platform Java application that serves as a code editor and compiler and is also capable of transferring firmware serially to the board. The development environment is based on Processing, an IDE designed to introduce programming to artists unfamiliar with software development. The programming language is derived from Wiring, a C-like language that provides similar functionality for a more tightly restricted board design, whose IDE is also based on Processing. The MQ series gas sensors are connected in a parallel manner with the VCC +5V, the ground pin and to the respective analog pin (A5 &A3) to the Arduino uno board. Afterwards, the Arduino Uno board needs to be programmed by scripting the sketch in C programming language & uploading the script to the microcontroller ROM. Once the I2C communication protocol & the SPI Communication Protocol has been established the sensor array starts reacting to the VOC gaseous mixture of the aroma from the target fruit (banana for this project) & the values for the dataset starts logging into the Data Acquisition Card (DAQ) – Secure Digital (SD) Card, configured with the Arduino Uno microcontroller board. The entire process of data acquisition is determined by the sequential computation of the instructions fetched by the microcontroller ATMega328P from the declaration of the SPI connection of the SD card to the digital pin ~10, ~11, ~12, ~13 & ~4 of the board to the initialization of the SD Card, creating separate folders for each of the dataset values. The Arduino Code for the data logging process is provided in this report with detailed explanation of the functioning of the header files along with the libraries called for the object modules and functions to be implemented in the scripting of the program file.

In the Arduino sketch, The library <SPI. h> is included in the program to initialize the SPI bus by setting SCK, MOSI, and SS to outputs, pulling SCK and MOSI low, and SS high. The <SD. h> Library in Arduino allows for communications between the Arduino Board and an SD Card Module for storage and retrieval of data. The analog output pin of the MQ3 & MQ7 gas sensor are connected to the analog pin A5 & A3 of the board. The chip select pin (CS) of the SD Card is connected to the digital pin number 4, hence an integer type variable named chipselect is declared at the beginning of the code starts by setting up the serial communication with a baud rate of 9600. The connection with the chipselect pin of the SD Card Adaptor is checked, via the if else loop using the <SD.h> library. When a secure chipselect pin connection is established, where the Arduino uno acts as the master & the SD card Adaptor as a slave in a SPI master slave connection, the SD card is finally declared to be initialized & a message pops up in the serial monitor of the Arduino uno IDE stating "the SD Card is initialized". The integer variable declared as gas sensor which stores the analog pin number on the microcontroller board to which the two gas sensors are wired namely analog pin A5 & A3 of the board, are declared as an input using the pinmode function. The void loop begins with three float type variables named sensor_volt that reads the change in DC voltage level of the MOS gas sensor as it changes with the difference in concentration of the target gas in aroma, a float type variable named rs_gas which reads the sensor resistance value of the target gas concentration present in the aroma, a float type variable declared as ratio which calculates & stores the ratio of the resistance value of the sensor in clean air to the resistance value of the target gas detected in the aroma. The integer variable sensorValue reads the analog values of the gas sensor using the analogRead () function. It then converts the analog values to voltage using the formula sensor_volt = sensorValue*(5.0/1023.0). The resistance of the gas sensor is then calculated using the formula "RS_gas = ((5.0*10.0)/sensor_volt)-10.0".

The ratio of the resistance of the gas sensor in a particular gas to the resistance of the sensor in fresh air is calculated using the formula "ratio = RS_gas/R0", where R0 is the sensor resistance in fresh air. The natural logarithm of the ratio is then calculated using the function log10() and used to calculate the desired PPM value of the gas using the formula "ppm_log = (log10(ratio)-b)/m" where m and b are the slope and y-intercept respectively in the logarithmic scale. Finally, the PPM value is converted back to linear scale using the pow () function and printed to the serial monitor using the Serial.println() function. In order to read the ppm values to the SD Card, an object declared as datafile is created of the File class belonging to the <SD.h> library. The object accepts the file name datalog.txt as a parameter & generates the datalog.txt file with the FILE_WRITE command directing the microcontroller to write the converted ppm values into the file. When the file is already present in the micro-SD Card, the SD. open () just accesses the file to read from it or write to it as per the command but if the file is not found to be present, it creates a memory space within the SD Card with the prescribed filename & performs the action as per the written command. The if else loop prints the ppm values sensed by each of the three MQ sensors, after calculation of the resistance in clean air to the gas resistance (R0/Rs) value thereby, converting it their natural logarithmic result by the above-mentioned equation in a comma delegated fashion as it's much easier for .txt to .csv format for further machine learning algorithms & for the dataset to be viewed in an excel format. Once, the file is opened in a datalogging process, it needs to be closed which is accomplished via the SD. close ().

The way of Machine Learning

Support vector machines (SVMs)

The SVM model or Support Vector Machine model is a popular set of supervised learning models that are used for regression as well as classification analysis. It is a model based on the statistical learning framework and is known for being robust and effective in multiple use cases. Based on a non-probabilistic binary linear classifier, a support vector machine is used for separating different classes with the help of various kernels. Support Vector Machines have significantly a much higher relative accuracy, as compared to more fundamental algorithms which means that when deploying the model in the real world. Moreover, due to the "kernel trick", the computation time of SVM support vector machines is reduced, which means that as data scientists, we are able to get better results in a reduced time while utilizing fewer resources. This is a win-win, as we can get better results without affecting hardware utilization costs and even at a faster time. we see better results from the machine learning models implemented. that can be leveraged while using decreased computation from the system.

Types of Support Vector Machines Algorithm

Linear SVM

The Linear Support Vector Machine algorithm is used when we have linearly separable data**.** When the dataset is such that it can be classified into two groups using a simple straight line, we call it linearly separable data, and the classifier used for this is known as Linear SVM Classifier.

Non-Linear SVM

When the data is not linearly separable then we can use Non-Linear SVM, which means when the data points cannot be separated into 2 classes by using a straight line (if 2D) then we use some advanced techniques like kernel tricks to classify them. In most real-world applications we do not find linearly separable datapoints hence we use kernel trick to solve them.

Terminologies in SVM Algorithm

Hyperplane

When given a set of points, there can be multiple ways to separate the classes in an n-dimensional space. The way that SVM works, it transforms the lower dimensional data into higher dimensional data and then separates out the points. There are multiple ways to separate the data, and these can be called Decision Boundaries. However, the main idea behind SVM classification is to find the best possible decision boundary. The hyperplane is the optimal, generalized and best-fit boundary for the support vector machine classifier. For instance, in a two-dimensional space, as discussed in our example, the hyperplane will be a straight line. In contrast, if the data exists in a three-dimensional space, then the hyperplane will exist in two dimensions. A good rule of thumb is that for an n-dimensional space, the hyperplane will generally have an n-1 dimension. The aim is to create a hyperplane that has the highest possible margin to create a generalized model. This indicates that there will be a maximum distance between data points.

Margin

It is the distance between the hyperplane and the observations closest to the hyperplane (support vectors). In SVM large margin is considered a good margin. There are two types of margins hard margin and soft margin.

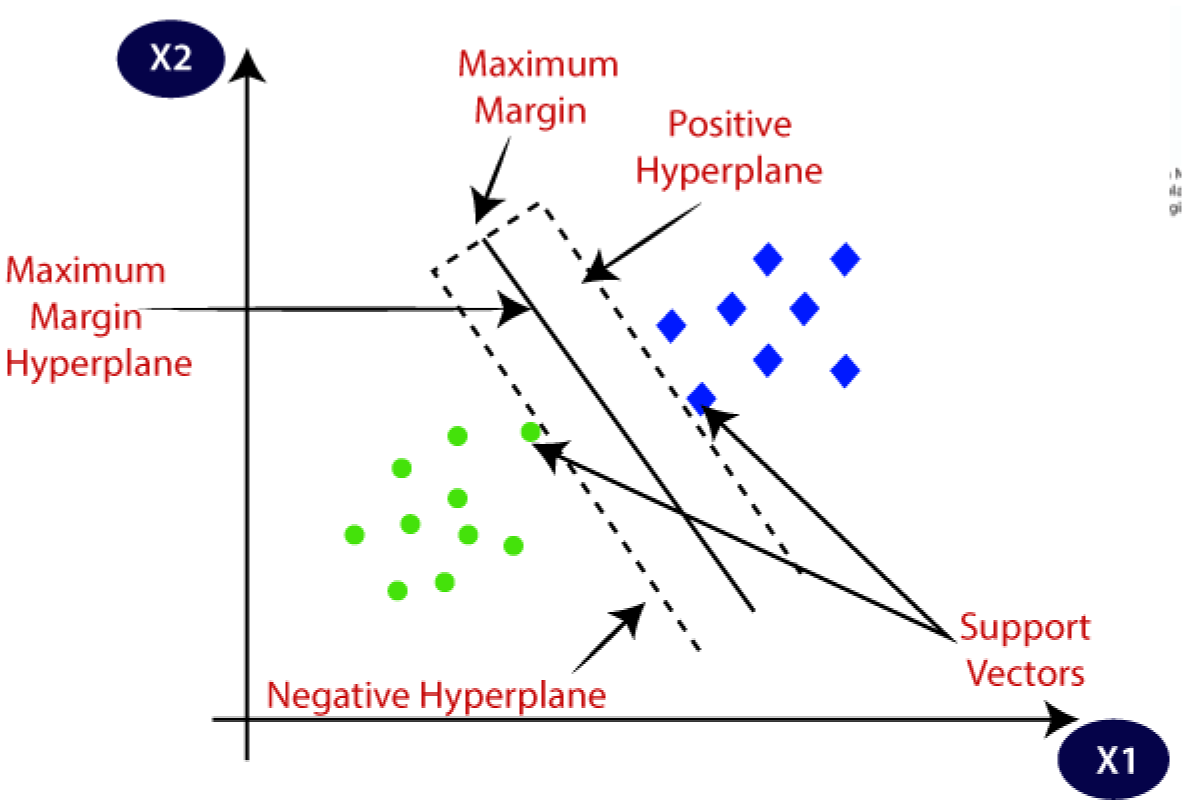


Figure 21 Margin in a SVM plot

Hard-margin SVMs

The best perceptron for a linearly separable data is called "hard linear SVM". For each linear function we can define its margin. The linear function which has the maximum margin is the best suitable producing accurate results.

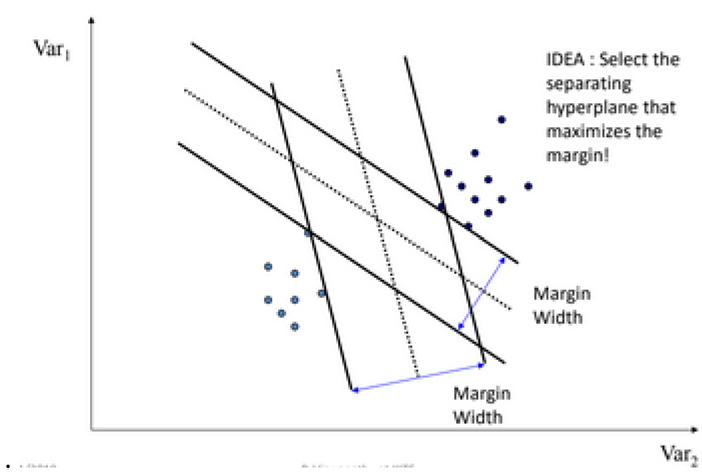


Figure 22 Hyperplane of the Hard-margin

Soft-margin SVMs

It allows for some mistakes with the training set in order to achieve a better margin.

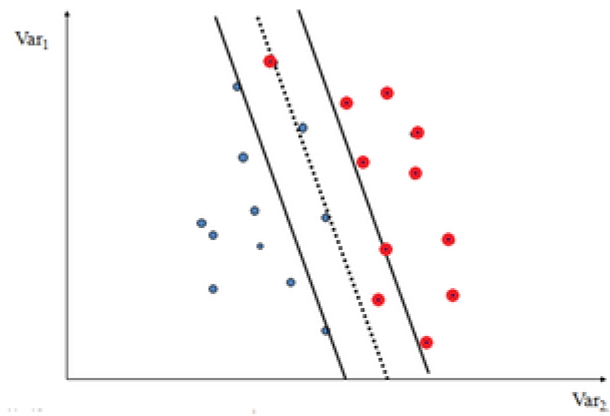


Figure 23 Hyperplane for the Soft-margin

Support Vectors

The term support vector indicates that we have supporting vectors to the main hyperplane. When the maximum distance between the support vectors exists , it is an indication of the best fit. Hence, support vectors are the vectors that pass through the closest points to the hyperplane and affect the overall position of the hyperplane. The vectors that define the hyperplane are the support vectors.

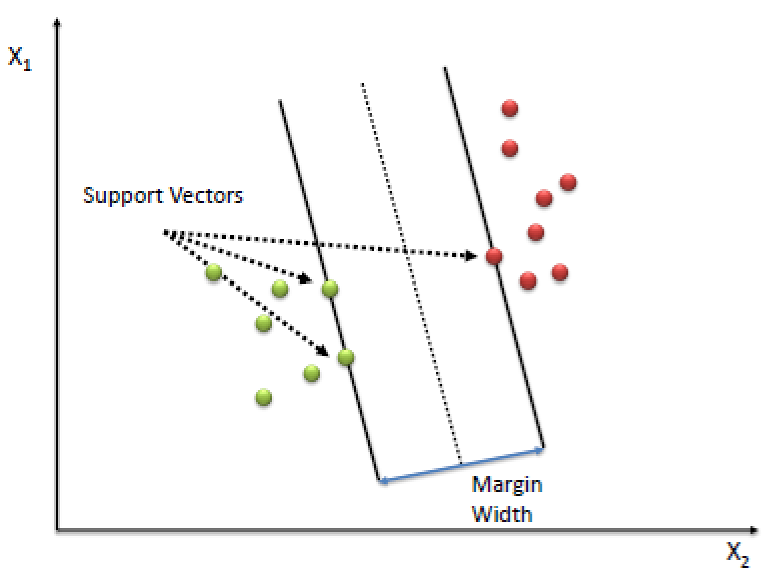


Figure 24 Support Vectors

SVM Kernel Functions

Linear Kernel Function

The linear kernel is primarily leveraged for linearly separable data. It is used for points that have a linear relationship.

Polynomial Kernel Function

The polynomial kernel function is used by leveraging the dot product and transforming the data to an n-dimension. This helps represent the data with a higher dimension leveraging newly transformed data points.

RBF (Radial basis Function)

This is one of the most common and widely used functions as a kernel, which behaves similarly to a weighted nearest neighbor model. It can transform the given data into infinite dimensions and then leverage the weighted nearest neighbor model to identify the observations that have the biggest influence on the new data point for the classification. The 'Radial' function in RBF can either be Laplace or Gaussian. We can decide this based on the 'Gamma' hyperparameter.

Sigmoid Function

The sigmoid function is found in use cases such as neural networks, where it is used as an activation function (Tanh). It is also known as the hyperbolic tangent function and has certain use cases where it can segregate the data better.

The Kernel Trick

The kernel trick is the "superpower" of Support Vector Machines. A Support Vector Machine uses kernels, ls, which is a function based on which the points can be segregated. The points that are no-linearly separable are projects to a higher dimensional space. When a SVM represents the non-linear data points in a fashion where the data points are transformed and then find the hyperplane.

However, the points remain the same, and they have not been transformed. This trick is the reason that the seeming transformation of the points from a lower to a higher dimension is known as the kernel trick.

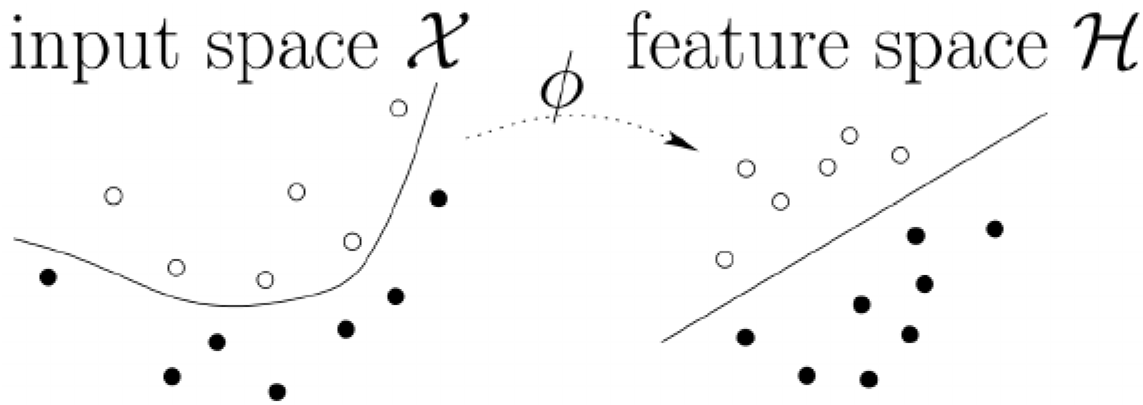


Figure 25 Mapping of input-space into feature-space

Support Vector Machine in a step-by-step fashion

The code for the Python script that trains and tests a support vector machine (SVM) classifier for volatile organic compounds (VOCs) from bananas and non-bananas. Here is a step-by-step explanation of the code.

Import necessary modules: The code begins by importing the required modules from scikit-learn, a popular machine learning library in Python. These modules include svm, which provides the SVM classifier implementation, and metrics, which provides functions to compute various performance metrics of the classifier. The code also imports train_test_split from model_selection module, which splits the dataset into training and testing sets.

Load and preprocess the dataset: The next step is to load the VOC measurements for bananas and non-bananas and preprocess the data. This is done by creating two empty lists to hold the VOC measurements for bananas and non-bananas, respectively. The code then iterates over the banana_voc_measurements and non_banana_voc_measurements list and appends each VOC measurement to the corresponding list. After that, it stacks the two lists vertically using np. vstack() and assigns the resulting array to X. Next, it creates a binary class label vector, y, by stacking two arrays of ones and zeros, corresponding to the bananas and non-bananas, respectively, using np. hstack ().

Split the dataset into training and testing sets: The preprocessed dataset is then split into training and testing sets using the train_test_split () function. The test size parameter specifies the fraction of the data to be used for testing, and the random state parameter sets the seed for the random number generator used for the split.

Train the SVM: The next step is to train an SVM classifier on the training set. The code creates an instance of the SVM classifier, clf, with a linear kernel, regularization parameter C=1, and class weight='balanced' (which balances the weights of each class to account for imbalanced data). The fit () method is then called on the classifier with the training data to train the model.

Test the SVM: The trained SVM model is then tested on the testing set. The predict () method of the classifier is called with the testing data to predict the class labels of the testing set. The accuracy, precision, recall, and F1-score of the classifier are computed using the corresponding functions from the metrics module, and printed to the console.

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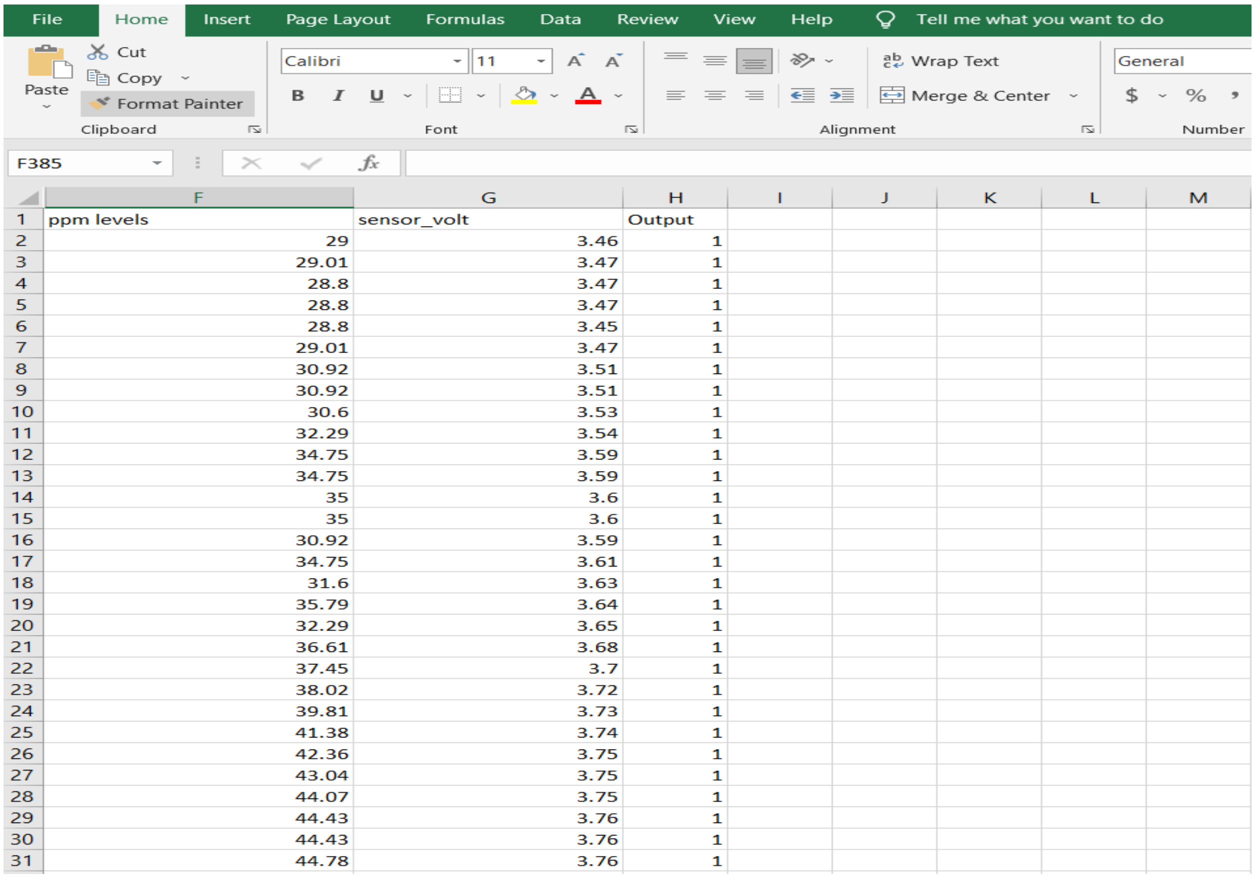
2. CHAPTER

RESULTS & DISCUSSION

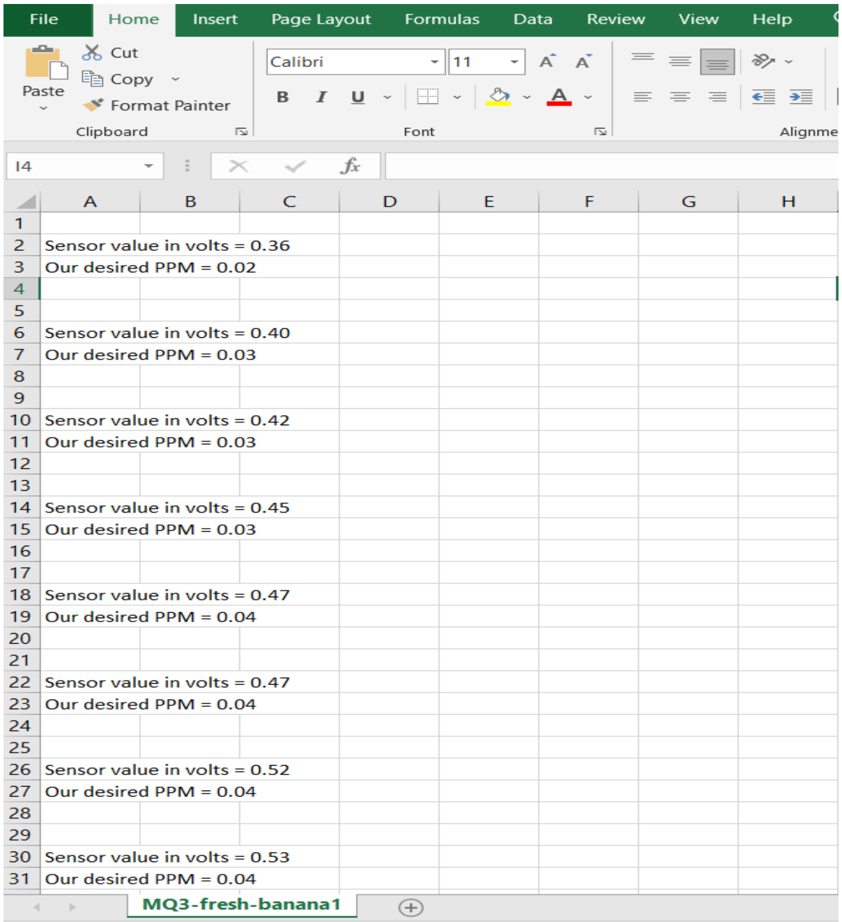


	ppm levels	sensor_volt	Output
2	29	3.46	1
3	29.01	3.47	1
4	28.8	3.47	1
5	28.8	3.47	1
6	28.8	3.45	1
7	29.01	3.47	1
8	30.92	3.51	1
9	30.92	3.51	1
10	30.6	3.53	1
11	32.29	3.54	1
12	34.75	3.59	1
13	34.75	3.59	1
14	35	3.6	1
15	35	3.6	1
16	30.92	3.59	1
17	34.75	3.61	1
18	31.6	3.63	1
19	35.79	3.64	1
20	32.29	3.65	1
21	36.61	3.68	1
22	37.45	3.7	1
23	38.02	3.72	1
24	39.81	3.73	1
25	41.38	3.74	1
26	42.36	3.75	1
27	43.04	3.75	1
28	44.07	3.75	1
29	44.43	3.76	1
30	44.43	3.76	1
31	44.78	3.76	1

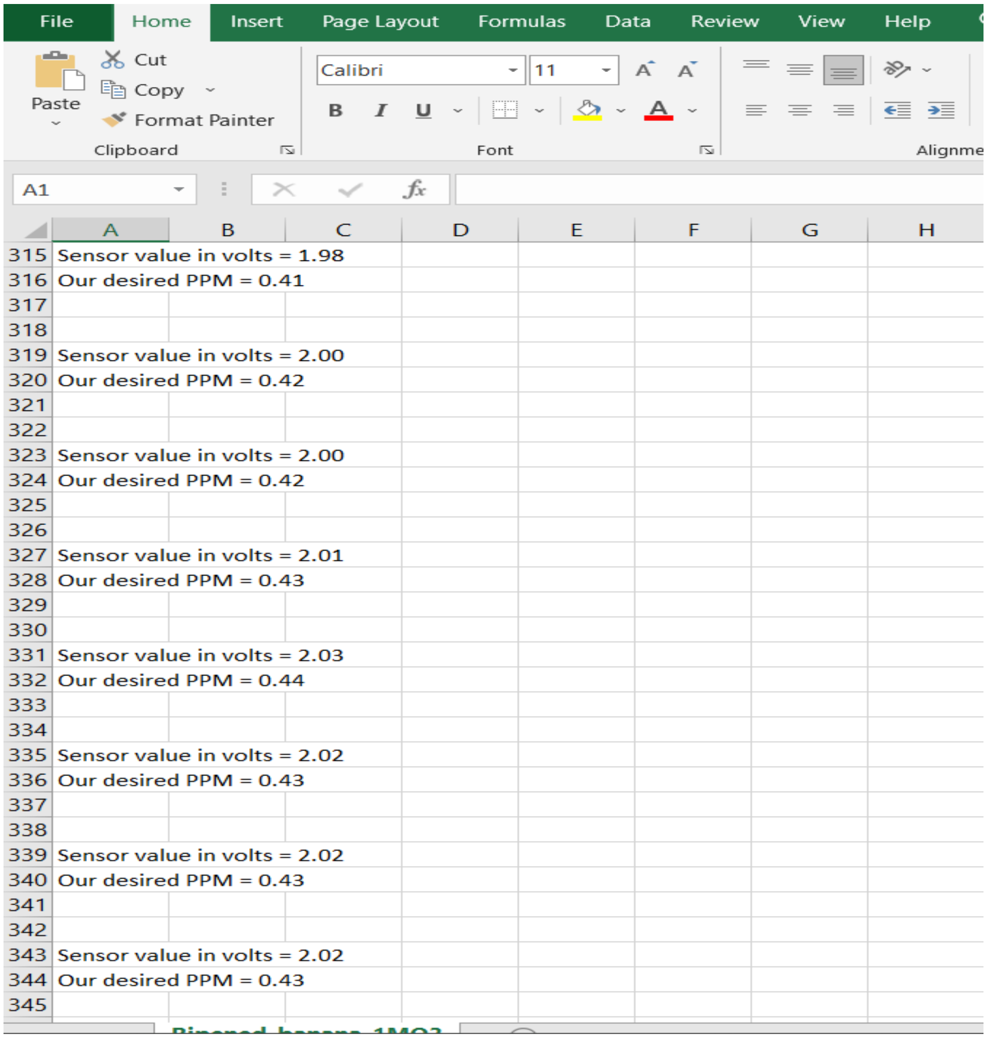
F385

	F	G	H	I	J	K
184	18.75	3.15	0			
185	19.12	3.17	0			
186	18.87	3.16	0			
187	13.96	2.92	0			
188	13.62	2.9	0			
189	16.51	3.05	0			
190	18.28	3.13	0			
191	19.37	3.18	0			
192	19.37	3.18	0			
193	19.24	3.17	0			
194	14.94	2.98	0			
195	13.28	2.88	0			
196	12.88	2.86	0			
197	12.88	2.86	0			
198	12.27	2.82	0			
199	12.05	2.81	0			
200	12.12	2.81	0			
201	11.98	2.8	0			
202	11.98	2.8	0			
203	11.9	2.8	0			
204	11.69	2.78	0			
205	11.9	2.8	0			
206	11.76	2.79	0			
207	11.76	2.79	0			
208	11.41	2.76	0			
209	11.48	2.77	0			
210	11.55	2.77	0			
211	11.55	2.77	0			
212	11.48	2.77	0			
213	11.34	2.76	0			
214	11.48	2.77	0			

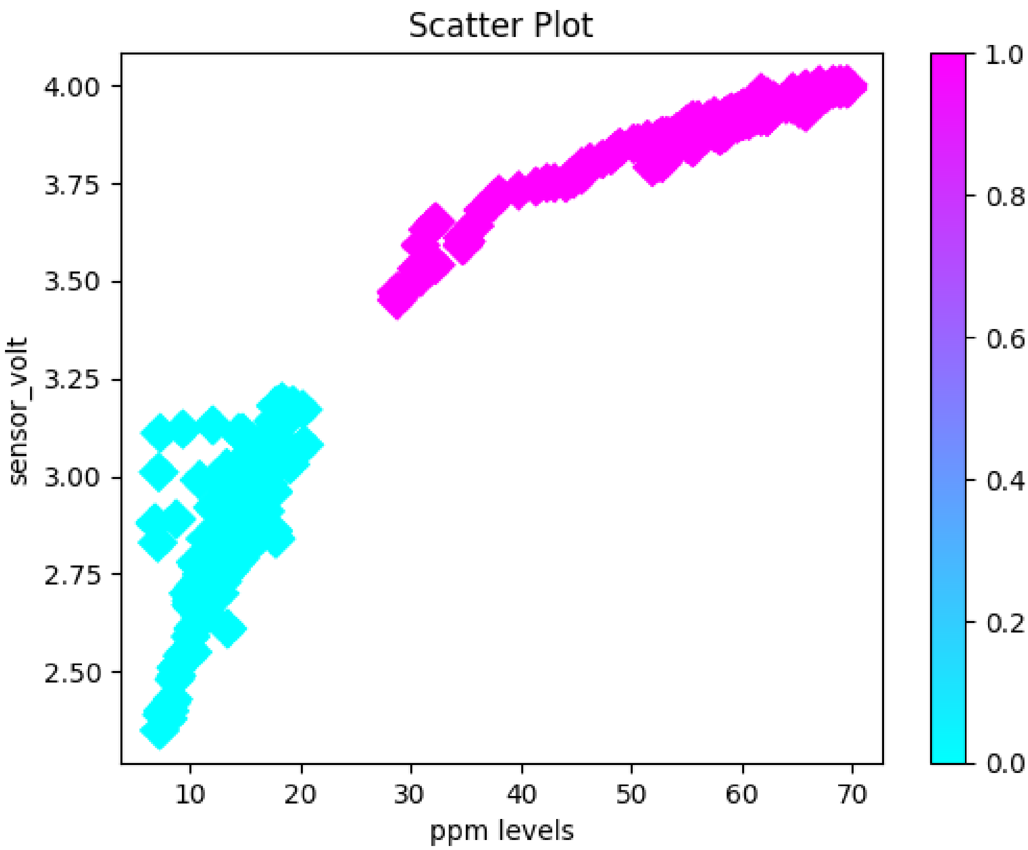
Sheet1 | CarbonMonoxidedatasheet_MIMO



	A
1	
2	Sensor value in volts = 0.36
3	Our desired PPM = 0.02
4	
5	
6	Sensor value in volts = 0.40
7	Our desired PPM = 0.03
8	
9	
10	Sensor value in volts = 0.42
11	Our desired PPM = 0.03
12	
13	
14	Sensor value in volts = 0.45
15	Our desired PPM = 0.03
16	
17	
18	Sensor value in volts = 0.47
19	Our desired PPM = 0.04
20	
21	
22	Sensor value in volts = 0.47
23	Our desired PPM = 0.04
24	
25	
26	Sensor value in volts = 0.52
27	Our desired PPM = 0.04
28	
29	
30	Sensor value in volts = 0.53
31	Our desired PPM = 0.04



	A
315	Sensor value in volts = 1.98
316	Our desired PPM = 0.41
317	
318	
319	Sensor value in volts = 2.00
320	Our desired PPM = 0.42
321	
322	
323	Sensor value in volts = 2.00
324	Our desired PPM = 0.42
325	
326	
327	Sensor value in volts = 2.01
328	Our desired PPM = 0.43
329	
330	
331	Sensor value in volts = 2.03
332	Our desired PPM = 0.44
333	
334	
335	Sensor value in volts = 2.02
336	Our desired PPM = 0.43
337	
338	
339	Sensor value in volts = 2.02
340	Our desired PPM = 0.43
341	
342	
343	Sensor value in volts = 2.02
344	Our desired PPM = 0.43
345	



Scatter Plot
4.00
3.75
3.50
3.25
3.00
2.75
2.50
sensor_volt
10
20
30
40
50
60
70
ppm levels
1.0
0.8
0.6
0.4
0.2
0.0

CONCLUSION

The classification performed is based on the dataset of MQ7 gas sensor and the results have been satisfactory and the aim of implementing an EN to sense the two VOCs CO & Alcohol from the aroma of the target fruit, storing the data values & design, train the non-linear SVM is successfully achieved. Although, the further mapping & prediction of the entire dataset with the ppm values of Alcohol, the model can be made more accurate for classification. This paper shows the advantages of IOT application in the field of food packaging & beverage industry, agriculture industry. The deployment of EN finds it's perfect compliments the advantages that edge IOT has which would make the instant smelling & detection of VOCs in the aroma of a wide range of food products regarding which the project can be further developed. Transferring human characteristics to non-living systems takes us one step closer to the science fiction stories in our dreams. The replication of human senses has been one of the most popular research topics for decades and the EN technology is a product of these long-term studies. The human olfactory system is extremely complex; however, it is not impossible to replicate. Since the day of the first prototype EN was developed, it has become a useful device in several applications, in solving urgent problems. Especially in the food industry and medicine, traditional ways of distinguishing subjects are too slow, expensive and mostly subjective which may result in fatal errors. The EN technology instead offers a fast, sensitive, low cost and objective alternative. Moreover, the potential of this new way of sensing is still rapidly growing with the new developments in sensors and machine learning technologies. An EN consists of two main components, the sensor array which is responsible for sensing the chemicals and algorithms which provide an analyzing software model in the system. There are several improvements required in both parts. More compact sensors need to be designed with the rising importance of wearable technologies. In the near future, the production of robust nano sensors for various tasks will presumably eliminate this difficulty. A further concern in ENs is the recalibration of sensors. Particularly, dynamic systems such as metal-oxide gas sensors require regular recalibration [296], which leads to time waste and high economic costs. Manufacturing stable sensors with durable materials will save time and money, especially in space missions, medicine and security applications

APPENDIX

Code for Arduino Uno:

```
#include <SPI.h>
#include <SD.h>

const int chipSelect = 4;
int gas_sensor = A5; //Sensor pin
float m = -0.754896547; //Slope
float b = 1.30; //Y-Intercept
float R0 = 1.04;
void setup () {
  // Open serial communications and wait for port to open:
  Serial.begin(9600);
  while (! Serial) {
    ; // wait for serial port to connect. Needed for native USB port only
  }



  Serial.print("Initializing SD card...");
//
//  // see if the card is present and can be initialized:
  if (! SD. begin(chipSelect)) {
    Serial.println("Card failed, or not present");
    // don't do anything more:
    while (1);
  }
  Serial.println("card initialized.");
```

```
  pinMode(gas_sensor, INPUT);
}

void loop () {
  // make a string for assembling the data to log:
  float sensor_volt; //Define variable for sensor voltage
  float RS_gas; //Define variable for sensor resistance
  float ratio; //Define variable for ratio
  int sensorValue = analogRead(gas_sensor);
  sensor_volt = sensorValue*(5.0/1023.0);
  RS_gas = ((5.0*10.0)/sensor_volt)-10.0;
  ratio = RS_gas/R0;
  double ppm_log = (log10(ratio)-b)/m;
  double ppm = pow (10, ppm_log);
  double percentage = ppm/10000;
  String dataString = "";

  // read three sensors and append to the string:
  for (int analogPin = 0; analogPin < 3; analogPin++) {
    int sensor = analogRead(analogPin);
    dataString += String(sensor);
    if (analogPin < 2) {
      dataString += ",";
    }
  }

  // open the file. note that only one file can be open at a time,
  // so, you have to close this one before opening another.
  File dataFile = SD. open ("datalog10.txt", FILE_WRITE);
```

```
  // if the file is available, write to it:
  if (dataFile) {
    dataFile.println(sensorValue);
    dataFile.println(",");
    dataFile.println(ppm);
    dataFile.close();

    Serial.println(sensorValue);
    Serial.println(ppm);
  }
// // if the file isn't open, pop up an error:
  else {
    Serial.println("error opening datalog10.txt");
  }
//}
}
```

Non-linear SVM Algorithm Model:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

from google.colab import drive
drive.mount('/content/drive')

df = pd.read_csv("/content/drive/MyDrive/qwe_Copy of CarbonMonoxidedatasheet_MIMO new(1).csv")

df. head()

df.isnull().sum()

df['predict'] = df['ppm levels'].apply(str) + ' ' + df['sensor_volt'].apply(str)

print(df['predict'])

X = df.drop(columns='predict', axis=1)
Y = df['Output']


print(X)
print(Y)

from sklearn import svm
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=56)

# Train the SVM
clf = svm.SVC(kernel='rbf', C=2, class_weight='balanced')
clf.fit(X_train, Y_train)

# Test the SVM
Y_pred = clf.predict(X_test)
accuracy = accuracy_score(Y_test, Y_pred)
precision = precision_score(Y_test, Y_pred)
recall = recall_score(Y_test, Y_pred)
f1 = f1_score(Y_test, Y_pred)
```

```
print("Accuracy: {}, Precision: {}, Recall: {}, F1-score: {}".format(accuracy, precision, recall, f1))

plt.scatter(df['ppm levels'], df['sensor_volt'], c=df['Output'], cmap='cool', s=100, marker='D')
plt.colorbar()
plt.xlabel('ppm levels')
plt.ylabel('sensor_volt')
plt.title('Scatter Plot')
plt.show()
```

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