

Introduction and Literature Survey

1.1. Introduction

Air-borne hazard detection and monitoring is a crucial area of research and development. Its motive is to provide safety for humans and the environment. Air-borne hazards may be toxic gases, particulate matter (PMs) and Volatile Organic Compounds (VOCs). These are dangerous for human well-being, the ecological system and industrial processes. The risk assessment can be very useful if we can accurately detect and monitor airborne hazards in real time. We can also implement timely mitigation strategies and issue early warnings in real time.

Such systems may contribute to the improvement of public health management, environmental protection and regulatory compliance. Hazardous airborne gases/VOCs/odors as released from industrial activities, transportation immission, wildfires, indoor pollutants can have severe consequences on human health, leading to various diseases like respiratory issues, allergies, cardiovascular diseases and even cancer. Accordingly, research and development in this direction are needed to enhance the capability of airborne hazard detection and monitoring systems to address the emerging challenges in this field.

The chemical sensors, particulate matter (PM) monitors, GC-MS, and Remote sensing techniques of distinct advantages in terms of sensitivity, selectivity, real-time monitoring and wide area coverage. However, each method has its limitation, such as restricted target analytes, maintenance requirements, cost considerations or limited applicability. Combining multiple methods and equipment can provide a comprehensive approach to airborne hazard detection and monitoring, leveraging their respective strains to ensure an accurate and reliable assessment of airborne hazards [110].

On the other hand, electronic noses (e-noses) have emerged as promising alternatives to traditional methods and equipment for airborne hazard detection and monitoring. E-noses utilise sensor arrays and pattern recognition algorithms to detect and identify VOCs present in the air. Their unique capabilities offer significant advantages over conventional techniques, making them preferable for airborne hazard

detection and monitoring. Their comprehensive detection capabilities, real-time monitoring, selectivity, sensitivity, portability, cost-effectiveness, and data analysis features make them highly preferable in various applications. By leveraging these unique capabilities of e-noses, we can enhance our ability to detect and monitor airborne hazards, leading to improved human safety, environmental protection, and effective risk management. Therefore, continued research and development in e-nose technology are crucial for advancing the field of airborne hazard detection and monitoring.

Considering its many potential applications, gas sensing is a hotbed of cutting-edge research in academia and industry. Nowadays, a wide variety of gas sensors are available. Numerous researchers have evaluated and contrasted the performance of various kinds of gas sensors. The gas sensors typically react to various VOCs, gases, and odors. Using a single gas sensor makes distinguishing between different VOCs, gases, or odors difficult.

Additionally, combinations of gases are something we encounter in the real world. In gas sensing, sensor arrays often provide better results than a single sensor. Electronic-nose (E-nose) is a notion developed by previous researchers using pattern recognition algorithms. After that, several more researchers proposed different ideas for better performance, such as a gas sensor array, intelligent sensor system, and machine learning algorithms to enhance the performance in real-time implementation.

1.2. VOCs/Gas/Odor Sensing

1.2.1 The Evolution of Gas Sensing

The researcher has to utilise gas sensing because of concerns about human health. The harmful gases have been shown to have severe adverse health impacts. As a result, gas detectors became needed to take preventative action before such a disaster. Hazardous gases, including carbon dioxide, carbon monoxide, and methane gas, which are highly hazardous to people, are often exposed in coal mines. In practice, the olfactory system is in the state of gas detection. The olfactory system is one of the five senses that people possess. However, the olfactory apparatus of a human being cannot detect odorless gases. Additionally, toxic gases in the air could be fatal to people because they cannot function without breathing, which is directly connected to

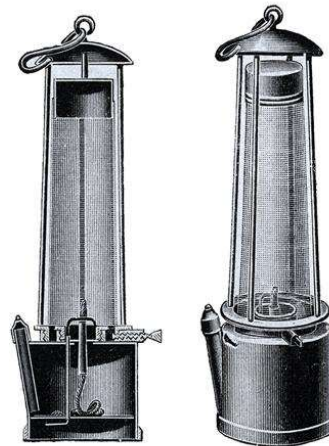
olfactory functions. The requirement for gas detectors is rendered possible by this constraint.

Gas detectors could be considered a safety system tool. These are extremely important because multiple gases can be harmful to people. The effect of dangerous gases on human health discovered the need for gas detectors. Early miners carry the canaries as an early warning against these toxic fumes. The canary birds chirp melodiously but stop when they smell these hazardous gases. Therefore, miners used the canary's silence as a warning of these hazardous emissions and as an indicator to quickly leave the mine.

Before sensors were invented, Sir Humphry Davy developed the first gas detector—the "Davy lamp". This lamp was developed to identify methane levels in mines. The Davy's lamp is the apparatus with the most extensive recorded existence in coal mines for gas detection [34]-[35]. Many researchers became motivated to create innovative gas-sensing devices and methods. Poor results have been generated by the gas detectors used before the electronic sensors. The development of electronic gas sensors and sensor arrays enhanced the field of gas sensing. Gas Detection with the canary bird and Davy's lamp is depicted in Figure 1. 1 (a) and (b).



(a) Coal miner with Canary bird



(b) Davy's Lamp

Figure 1.1 (a) Coal miner with Canary bird and (b) Davy's Lamp for Gas Detection in Coal mines

1.2.2 Gas Chromatography-Mass Spectrometry (GC-MS)

GC-MS is a powerful analytical technique for identifying and quantifying chemical compounds in complex mixtures. GC-MS combines the separation capability of gas chromatography (GC) with the detection and identification capabilities of mass spectrometry (MS). Due to its high selectivity, sensitivity and versatility, this equipment has become a widely adopted method in various scientific disciplines, including environmental science, forensics, pharmaceutical analysis, and chemistry.

In the GC steps, Firstly, the sample is vaporised and injected into a gas chromatograph, separating the mixture into its individual components based on their volatility and affinity for the stationary phase. The separated compounds are then introduced into mass spectrometry. The MS consists of an ionisation source, mass analyser and detectors. The ionisation source ionises the separated compounds, typically through electron ionisation (EI) or chemical ionisation (CI). The resulting ions are then accelerated into the mass analyser, which separates them based on their mass-to-charge ratio (m/z) [69]. The detector detects the separated ions, generating a mass spectrum representing each compound's unique pattern of ions.

The GC-MS has high sensitivity at trace levels and is as low as parts-per-billion (ppb) or parts-per-trillion (ppt). It provides high selectivity and specificity in compound identification. It can be used to analyse a wide range of volatile, semi-volatile compounds, including organic compounds, environmental pollutants, drugs, metabolites, and fragrance compounds. However, despite its multiple advantages, GC-MS requires specialised steps for sample preparation, e.g. extraction, derivatisation or concentration, to ensure efficient separation and detection of the target compounds. These steps are usually time consuming and may introduce potential sources of error. GC-MS is also very expensive, both in terms of capex (capital investment/expenditure) and opex (operational cost/expenditure). The Schematic Block diagram of Gas Chromatography and Mass Spectroscopy is shown in Figure 1.2.

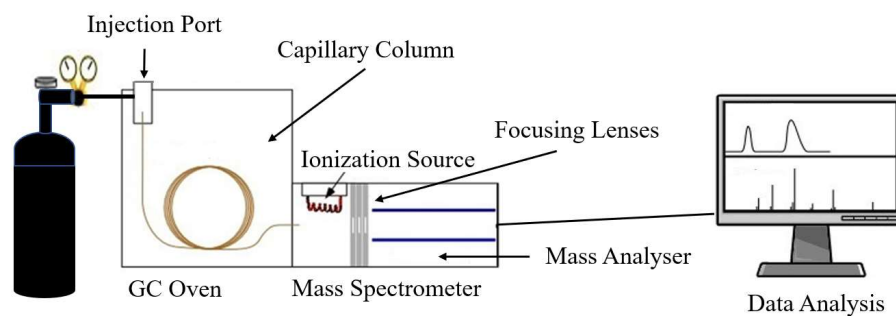


Figure 1.2 Schematic Block Diagram of Gas Chromatography and Mass Spectroscopy.

1.2.3 Mammalian Olfactory System

Since smell is a subjective phenomenon that vertebrates cannot quickly examine, it is the least understood of our senses. Furthermore, compared to many other vertebrates, humans have a poorly developed sense of smell. The olfactory cells, bipolar nerve cells initially generated from the central nervous system and found within the olfactory bulb, are the receptors that provide the olfactory knowledge. These cells comprise the olfactory epithelium, which has roughly 100 million neurons. Humans have three sensory systems: olfaction (the sense of smell), gustation (the sense of taste), and the trigeminal system, which is sensitive to irritating chemical species. Among them, smell plays a significant role in how we sense flavor. Nearly all living things, including plants and people, have developed the ability to sense the molecules in their surroundings [8], [24].

Researchers have demonstrated an intense curiosity in recent decades in trying to comprehend and realise the actual reality of the olfaction system. Numerous diverse and integrative processes, including physical control, emotional reactions, reproductive processes, and social behaviors, are regulated by the olfactory systems in mammals and other vertebrates [25]-[26].

The nose inhales the odorant molecule and passes through turbinate, curved bony structures that induce turbulent flow that carries odorant molecules to the olfactory epithelium's thin mucus covering. The olfactory epithelium, which detects odorants, displays the terminals of nerve cells [10].

The olfactory sensory neurons, sustentacular or supporting cells, and basal cells are the primary cell types found in the neuroepithelium, which is situated at the back of the nasal cavity's recesses. Olfactory neurons are produced throughout life and are

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created in the basal cell. They are replaced around every 30 days. A dendritic process from the bipolar sensory neurons in the epithelium extends to the mucosal surface. They are coated with cilia, which resemble hairs and have receptors on the cell's outer membrane [27].

The odorant attaches to a particular surface receptor protein known as a G protein, [28] which starts an enzyme cascade reaction that depolarises the cell membrane. These responses lead to the formation of action potentials, which flow through the axons of the olfactory sensory neural wires. These axons branch to the brain's olfactory bulb and end in glomeruli, a collection of neural networks. Dendrites from around 25 giant mitral cells and 60 smaller tufted cells also terminate at each glomerulus. The initial layer of the central odor information processing is represented by more than 2000 such glomeruli in the olfactory bulb.

The epithelium's olfactory sensory neurons may react to various odorants, which results in a pattern of response over several glomeruli that reflects the olfactory system's quality. The higher level of the brain is eventually where this olfactory information is processed [27]. Multiple odorants can elicit different responses from olfactory neurons in the epithelium. Therefore, the response pattern across various glomeruli determines the qualitative parameters of olfaction [29]. The following brain processing improves sensitivity and allows distinguishing various smells because of its parallel design and distributed memory [8]. The mammalian olfactory transduction mechanism is depicted in Figure 1.3.

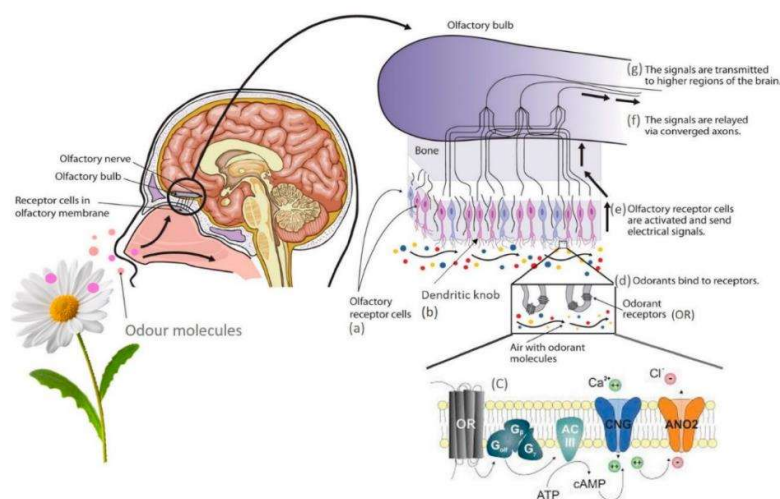


Figure 1.3 Schematic representation of mammalian olfactory transduction mechanism [30]

1.2.4 Artificial Olfaction and Electronic-nose (E-Nose)

Recent advances in research emphasise developing electronic nose (e-nose) systems and highly efficient olfactory devices. The necessity for the classification of odorants in a highly effective way has been promoted by improvements in the fields of medicine, food industry safety and security, manufacturing, war weapons, and pollution, among several others. To prevent accidents in both public and private locations, one must maintain surveillance on the leakage of flammable and toxic gases, odors, and volatile organic compounds (VOCs) [5]-[6]. Most chemical pollutants are monitored using traditional methods, which are costly, lengthy, complicated, and only use limited sampling and analytical techniques. Therefore, there is a natural need for low-cost, improved, and trustworthy methods that can quickly and accurately detect harmful explosive VOCs, gases, and odors before they cross the safe limit and inhibit the occurrence of any fatal accidents. By providing relatively affordable, portable odor detection devices with a wide range of organic, inorganic, gaseous, and chemical pollutants, e-nose technology advancements over the past few decades have explored better quality control capabilities to monitor chemical pollution in various environments [7]. Modern gas sensing technology is based on the olfactory system of mammals. Mammalian olfaction systems are complicated, and researchers are still trying to comprehend them fully.

Researchers have been keen on artificially mimicking the olfactory system for a decade, motivated by the prediction established for the mammalian olfactory system. In the earliest days of history, the human nose served as the primary tool for odor identification. Before the development of artificial olfaction, human panels were used to assess the aroma of things like perfume, food, and beverages [8]. However, individual variation, adaptation, fatigue, infection, mental state, subjectivity, and exposure to toxic substances were problems with human professionals. Additionally, using a human panel is expensive because they only have short lives.

Each sensor in the sensor array has a distinct sensitivity to various odors, which is the primary operating concept of an electronic nose. This is done to replicate the olfactory system of mammals, which has sensory neurons in the epithelium that may react to aromas differently depending on their sensitivity. For various odors, the sensor

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array's response pattern differs. The sensor array's response pattern essentially serves as a signature pattern for a particular gas. As a result, the array's sensors each have a distinct character for the range of odors being tested [10].

Artificial olfaction, an electronic nose system, has received much academic attention over the last several decades to replicate how the mammalian olfaction system processes information. Considering the hazards of toxic, hazardous, and explosive gases, artificial olfaction must be efficient and precise enough to detect VOCs, gases, and odors before they exceed the permitted level and prevent fatalities [11].

In 1982, Presuad and Dodd developed the idea of an electronic nose (E-nose) [4]. Since the human olfactory system is very effective at identifying odors, the aim was to mimic human olfaction [12]. Researchers have worked to artificially integrate gas sensors for decades to mimic an authentic nose's accomplished range of functionality. An e-Nose in this scenario uses various non-selective gas sensors, signal conditioning/pre-processing, and pattern recognition algorithms. Finally, a pattern recognition method was used to leverage intelligence or the brain. The biological olfactory and artificial E-nose systems as shown in Figure 1.4.

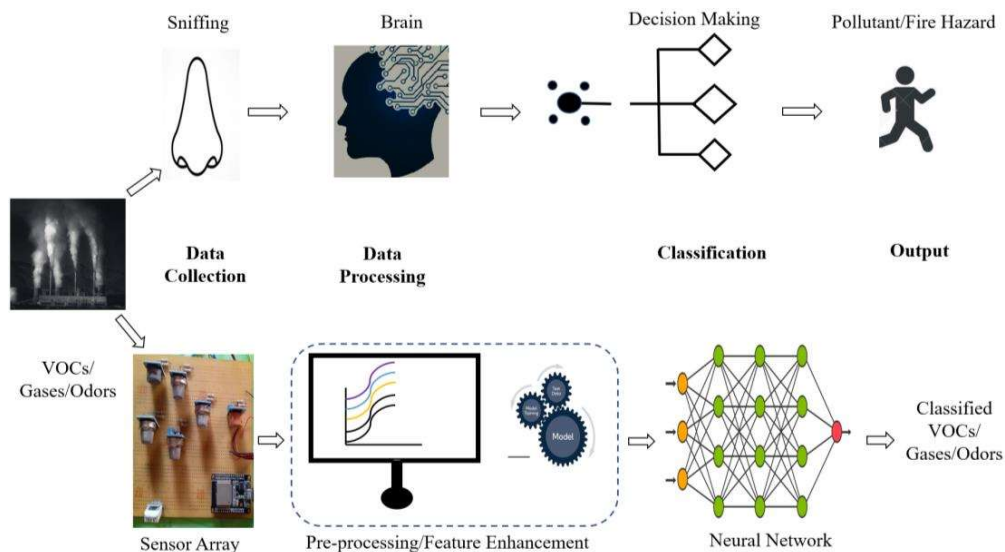


Figure 1.4 A Comparison of the biological olfactory and artificial E-nose system.

1.2.5 Application of E-nose for Air-Borne Hazard Detection

The VOC, gas, or odor-detecting method utilized in the e-nose mimics the human olfactory system. It represents the system's hardware component and uses various gas sensors to identify the VOCs, gases, and odors. The diversity of applications shows that the e-noses are multilateral. A schematic view of gas sensing applications is shown in Figure 1.5.

The following is the corresponding list of applications:

- Environmental Protection: Pollution Hazard detection, Fire Hazard Detection and Monitoring [138], Indoor gas monitoring [20]-[21], Outdoor gas monitoring [22]-[23]
- Home Appliances: Indoor Air Quality Monitoring [135], Hazardous gas detection [137]
- Transport: Vehicle health monitoring [134], Automobile exhaust detection [18]-[19]
- Medical and Forensics: Asthma [122], Cancer [123], Tuberculosis [124], Sinusitis [125], Covid-19 [126], Remote health monitoring [139], other disease prediction [16]-[17]
- Agriculture: Crop health prediction, grain quality assessment [127], agricultural product quality inspection [128], vegetable/edible oil assessment [129]
- Safety and Security [121]
- Industries and Robotics: Food Quality [120], Alcohol characterisation [132], Cosmetics [133], Beer flavour monitoring [131], Fish and meat quality [13]-[14], Drugs Classification [15], Robotics [130], refinery environment [136]

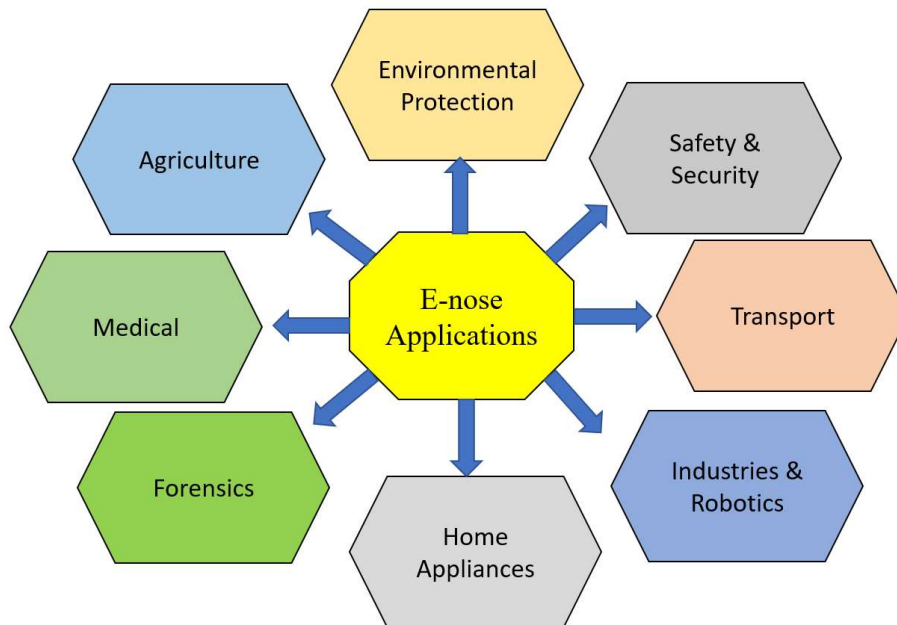


Figure 1.5 A Schematic view of Gas sensing Applications

1.3 Recent Advancements

In recent advancements, sensor technology refers to using electronic devices, such as sensors, to detect and respond to changes in the physical environment. Sensors convert physical, chemical, or biological signals into electrical signals, which can be measured, processed, and analysed.

There are many types of sensor technology, including in our research work:

- Temperature and humidity sensors: Used to measure temperature and humidity changes in the environments
- Gas Sensors: Used to detect the presence of gases or vapors in the air
- PM Sensor: For particulate matter (PM) detection

1.3.1 Sensor Technology

There are several uses for gas sensing at the present moment. The gas sensors were helpful in various circumstances because of their adaptability. Some standard gas sensing applications include environmental safety monitoring, residential air pollution detection, fire hazard detection and monitoring, health hazard detection (through breath analysis), safety and security, agricultural monitoring, drug detection, food industries, coal mines, etc.

Researchers Brattain and Bardeen et al. studied how the gaseous environment affects semiconductors' electrical characteristics. To see that the contact potential varies depending on the gaseous environment, they conducted several experiments using Germanium (Ge). They observed that interaction with the gaseous environment changes semiconductor materials' electrical properties (resistance). The change in resistance indicated that semiconductor materials were being used for gas detection [1]. The interaction of a gas molecule with a thin film metal oxide face for adsorption and desorption has been found by Seiyama et al. The phenomenon changes the semiconductor's electrical properties significantly, making it possible to detect gases [2]. Taguchi patented a device that could detect smoke and flammable gases. A metal oxide semiconductor (MOS) element was included in this device. When exposed to gases, the MOS device's electrical resistivity changes. The tin oxide was a sensing material in the first metal-oxide-semiconductor gas sensor. Due to its higher sensitivity, lower operating temperature requirement, and thermal stability, the tin oxide was selected over other metal oxides [3]. The term "Electronic Nose" was initially used by Presuad et al. when they created a model nose for gas/odor discrimination. Three gas sensors were included in their array. They observed that a consistent sensor system might be created without requiring highly specialised sensors to distinguish between gases or odors [4].

Catalytic Gas Sensor: The most common commercial type of pellistor is the catalytic sensor, which measures the heat created from the catalytic oxidation of the gas analyte. They burn the target gas and produce a particular combustion enthalpy, enabling quick reaction time and detecting analytes with low concentrations. The catalytic sensors improve accuracy and allow integration into detection systems as the flame safety

lamp's replacement for detecting flammable gases, as shown in Figure 1.6. However, they continue to suffer from a severe issue known as catalyst poisoning when certain impurities are present in gas samples, which results in a significantly reduced and occasionally irreversible loss of catalyst activities [38]-[39].

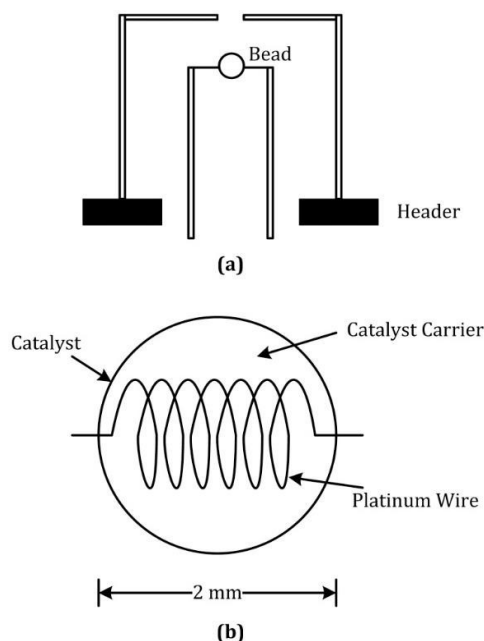


Figure 1.6 Catalytic Gas Sensor (a) Schematic diagram and (b) configuration of ceramic bead [38]-[39]

Electro Chemical sensor: The detected molecules perform a redox reaction on a suitable electrode on an electrochemical gas sensor surface, producing an electrical current based on the gas concentration. As a receptor, the sensitive layer from the detecting surface functions. In some instances, combustion or other chemical activities involving electron transfer follow particular functional surface groups' adsorption or chemisorption of the identified species. The transducer converts the atomic-scale contact into an electrically detectable response and is connected to the receptor. Electron density, optical characteristics, mass, and temperature are physical characteristics of the receptor surface that vary due to the interaction with the molecules being sensed. Most electrochemical sensor systems use semiconductive metallic oxides (SMO) as the receptor, and changes in electronic charge density and charge carrier mobility occur due to gas interaction [41]. The Schematic Circuitry of the Electrochemical Gas Sensor is shown in Figure 1.7.

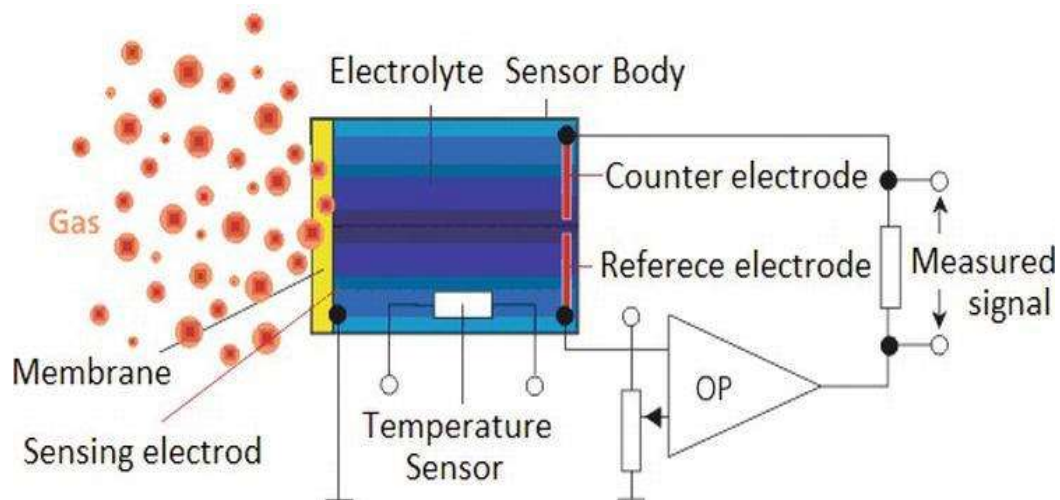


Figure 1.7 Schematic Circuitry of Electrochemical Gas Sensor [41]

NDIR Sensor: Several applications for infrared (IR)-source gas sensors operate on optical sensing principles. The fundamentals of absorption spectrometry, particularly the molecular absorption spectrometry concept, are the foundation of IR-source gas sensors. It means that each gas has a unique IR absorption fingerprint and its absorbing characteristic to IR radiation of various wavelengths. Three primary components comprise an IR-source gas sensor: an IR source, a gas chamber, and an IR detector. The sample gas in the gas cell will absorb the radiation uniquely when the IR source provides broadband radiation that includes the wavelength the target gas absorbs. The optical filter blocks all light except for the wavelengths absorbed by the target gas. As a result, an IR detector may find and quantify the existence of an exciting gas. This is also known as Non-Dispersive Infrared (NDIR) gas sensor [39]. The Schematic of the Non-dispersive Infrared (NDIR) Gas Sensor is shown in Figure 1.8 (a) the elemental absorption spectrometry and (b) with reference filter/detector.

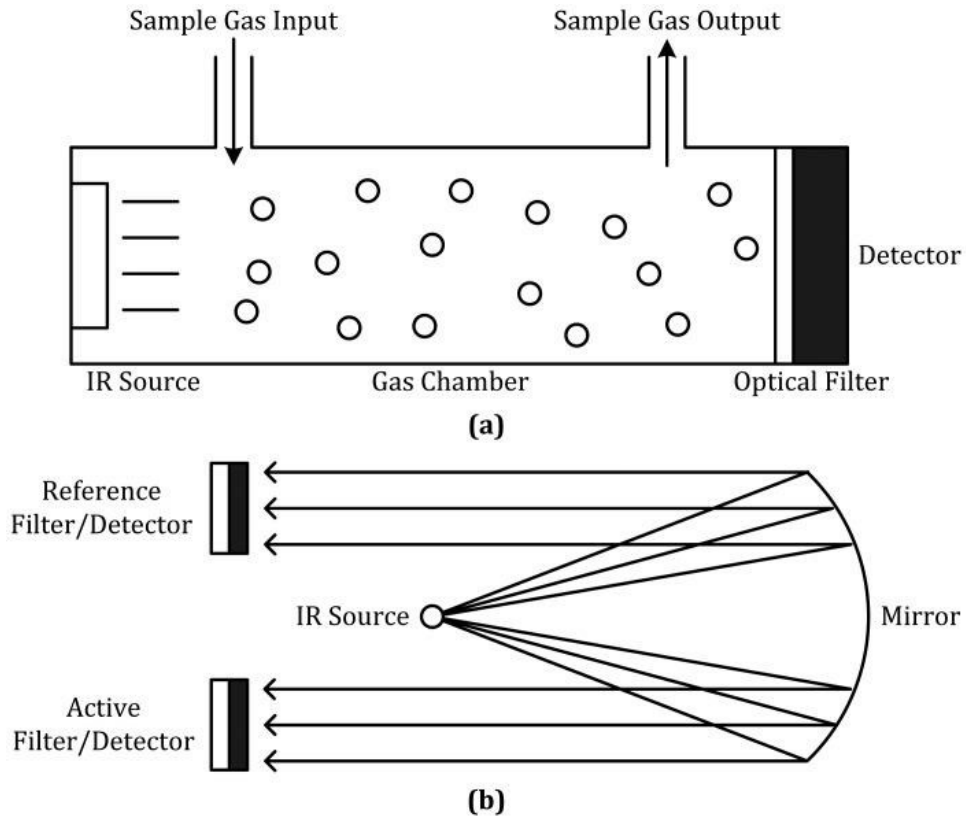


Figure 1.8 Schematic of Non-dispersive Infrared (NDIR) Gas Sensor (a) the elemental absorption spectrometry and (b) with reference filter/detector [39].

QCM Gas Sensor: The mass sensitivity of the QCM is dependent on the crystal's thickness. The shear stiffness of the crystal and the resonant frequency are inversely proportional to each other based on Equation (2). Therefore, to achieve high resonance frequency in QCM, the thinner quartz resonator is required to lower μ_q , the shear stiffness, and enhance sensitivity. However, the use of thin film can be limited due to the difficulty in the fabrication process. Surface mass changes cause the resonance frequency change [42]. The Schematic view of QCM Gas Sensor is shown in Figure 1.9. Where f_0 , ρ_s , μ_q , and ρ_q are the reference resonant frequency, the surface mass density, shear stiffness, and the density of quartz, respectively.

$$\Delta m = -C \times \Delta f \quad (1)$$

$$\Delta f = \frac{-2f_0 \times 2\rho_s}{\sqrt{\mu_q \times \rho_q}} \quad (2)$$

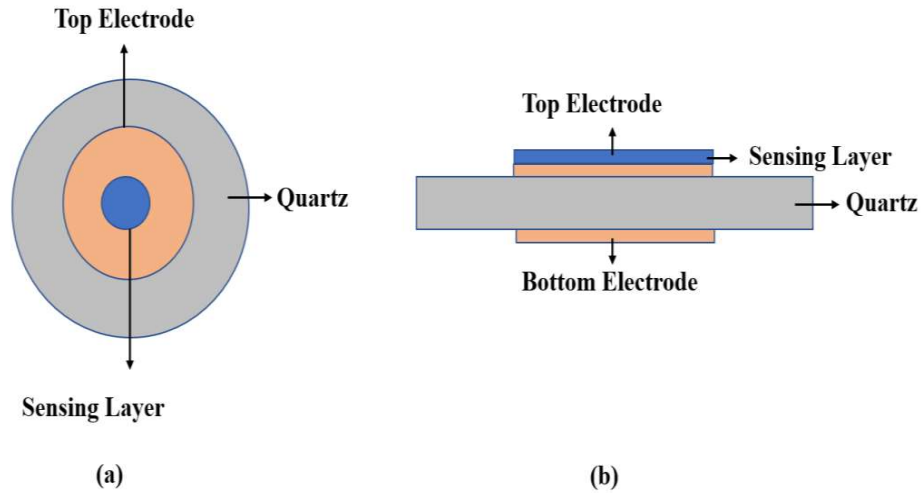


Figure 1.9 Schematic view of QCM Gas Sensor (a) top view and (b) side view [42]

MOX Sensor: Semiconductor gas sensors are sensors used to detect the concentration of a target gas by measuring the electrical resistance of the instrument, which is made up of heated metal oxides. They operate on the principle of reversible gas adsorption at the surface of heated oxides, typically oxides of tin formed by chemical vapor deposition technique on a silicon slice [45]. The Schematic of the Metal-Oxide Semiconductor (MOX) Gas Sensor is shown in Figure 1.10.

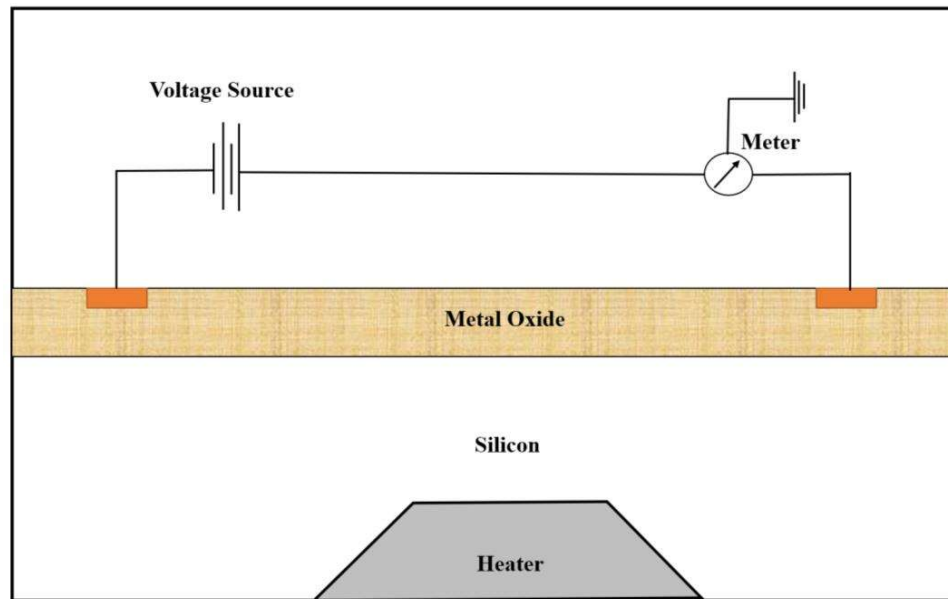


Figure 1.10 Schematic of Metal-Oxide Semiconductor (MOX) Gas Sensor [45]

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In general, exposure to the target gas changes the electrical conductance/resistance of the metal oxide-based conductometric gas sensors. The properties of the target gas and the sensitive materials control the rise or decrease of electrical resistance. This curve states that exposure to a gas analyte causes a change in conductance or resistance. The airflow can be restored once the sensor reaches a stable conductance value while the gas is present and the sensor returns to its initial value [46]. The response and recovery times of the sensors are shown in Figure 1.11.

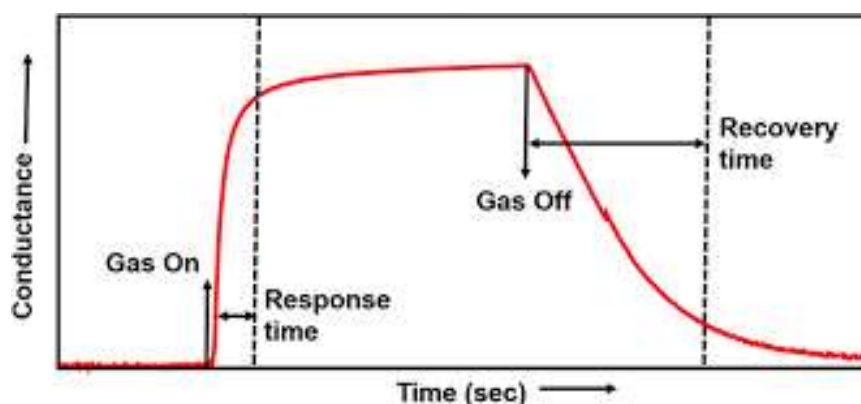


Figure 1.11 Typical Response Curve of Gas Sensor [46]

The resistor that heats the sensing surface to facilitate effective redox reactions between the adsorbed molecules of the target gas and the metal oxide is the primary power consumption in MOX sensors [43]. Manufacturing technology development has made it possible to miniaturize the heater resistor and detecting chip, resulting in more compact and power-efficient sensors. MOX sensors may currently be produced with a highly compact form factor and power consumption of only tens of milliwatts [44]. The evolution of metal oxide semiconductor (MOX) technology in size and power efficiency is shown in Figure 1.12.

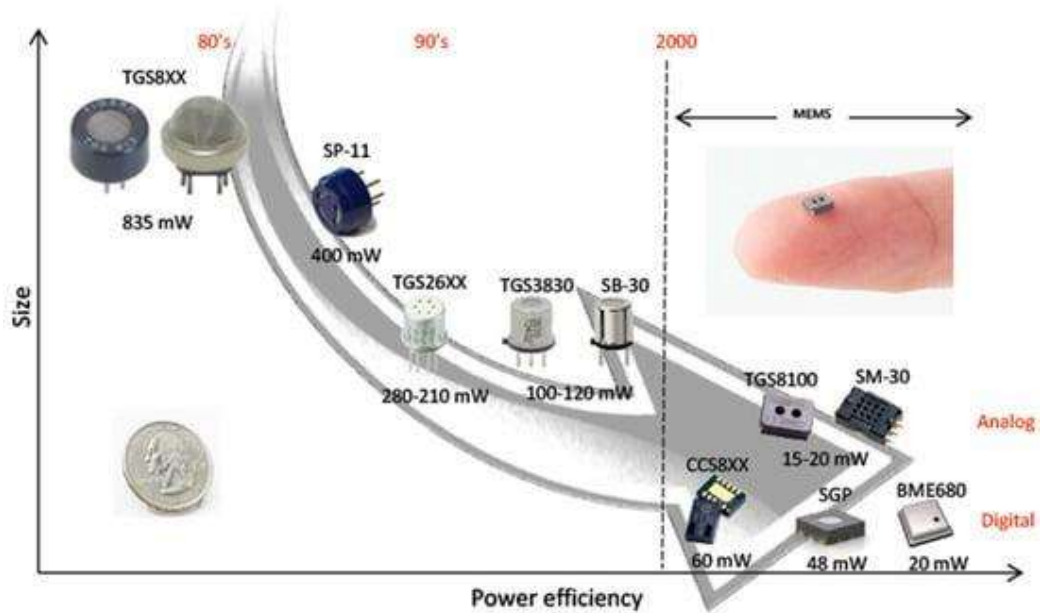


Figure 1.12 Evolution of metal oxide semiconductor (MOX) technology in size and power efficiency. The background arrow indicates the temporal evolution [43]-[44].

The current trends in resistive-based gas sensors are based on their energy consumption point of view [40], as shown in Figure 1.13.

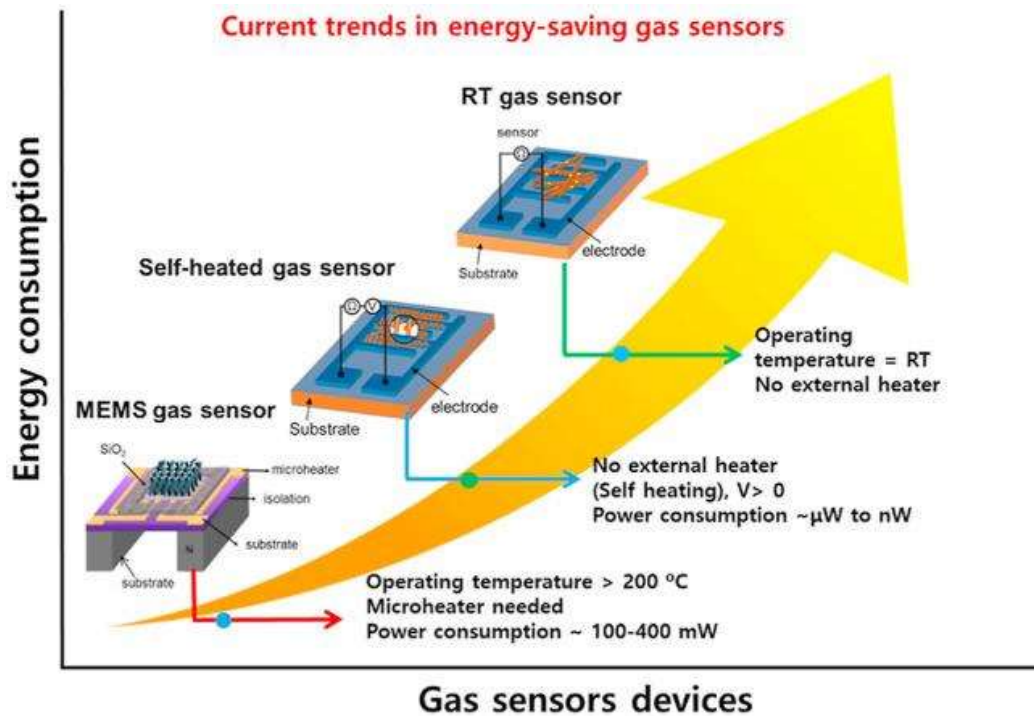


Figure 1.13 Resistive gas sensors and their energy consumption graph [40]

1.3.2 Tin-Oxide MOX-Based Gas Sensor Array

Gas sensors are designed to detect particular VOCs, gases and odors. The natural environment comprises a combination of gases, and gas sensors are also cross-sensitive to other gases. Consequently, each gas sensor performs as a non-selective gas sensor for the other gases outside those that were anticipated when the sensor was established. With this conclusion in thoughts, a model nose comprising several general-purpose gas sensors was developed in the early 1980s. This study demonstrated that non-selective sensors might simultaneously achieve high-performance gas discrimination instead of specific gas sensors [4]. The design and development of the artificial olfaction system, or e-Nose, was made possible by this revolutionary usage of the gas sensor array.

Gas sensors based on metal-oxide semiconductors (MOS) have been investigated for a long time. A metal oxide semiconductor field effect transistor (MOSFET) with a palladium gate was the first MOS-based gas sensor, and it was used to detect hydrogen gas [31]. Since then, the study of MOS devices with different transition-metal gate electrodes has focused mostly on gases that include hydrogen and some CO gas. These sensors are appropriate for mass production due to their foundation in conventional microelectronic manufacturing technology, resulting in a very cheap cost per unit. The barrier's permeability is crucial for the MOS sensor's sensitivity to gases such as CO, alcohol, ammonia, and a broad spectrum of hydrocarbons. This indicates that an apparent number of cracks should be present in the morphology of a metal gate. The sensitivity, selectivity, and stability of MOS gas sensors are being improved by further research. This technology is used in the PEN-3 for Airsense Analytics and Fox 4000 from Alpha MOS, commercially available e-noses [32].

By applying the idea of a change in conductance due to gas adsorption on a semiconductor surface, which W. H. Braittain had previously established, Nayoshi Taguchi was the first to present work in the arena of gas sensors [1]. The primary material for the Taguchi sensor was zinc oxide. Still, as the decades passed, tin oxide-based gas sensors gained popularity because of their high sensitivity to reducing and oxidizing gases [33]. The Osaka-based Figaro Engineering Company developed the Taguchi gas sensor, often known as the TGS. The sensor comprises a ceramic (alumina)

tube with a gold electrode design coated with a gas sensing layer. A gold alloy coil heating element is also threaded inside the tube to maintain the necessary operating temperature (typically between 200° C and 400° C) for the sensor to operate correctly. As indicated earlier, multiple dopants are constantly added to the tin-oxide base material depending on the catalysts' needs to increase the sensors' selectivity and sensitivity because of the non-selective behavior of the gas basic sensitive layer (tin oxide). The substrate is typically installed on a TO socket with the other required setups. The Figaro-type sensors have a power consumption range of 0.6 to 1.2 W, and such sensors are still available on the market.

A tin-oxide MOX-based gas sensor array is a type of gas sensor that utilises metal oxide semiconductor (MOX) technology to detect the presence of gases in the environment. Tin oxide (SnO₂) is a standard metal oxide semiconductor material used in gas sensor arrays due to its high sensitivity to many gases, such as hydrogen, carbon monoxide, and methane.

Implementing of gas sensor array has resolved the poor selectivity problem with most sensor sections. Additionally, using multiple sensor elements improved the ability to detect a broader range of VOCs because a single sensor element can only detect a limited number of chemical analytes. Since then, many researchers have created several methods for detecting gases and odors utilising sensor arrays [36]-[37]. They have created a portable device with an array of gas sensors that detect gases and odors via a pattern of electrical responses. The hazardous component present in the air was then determined by comparing these sensor-formed response patterns to the standard. This experiment shows that a collection of compact sensors generates patterns of response that may be compared to a standard response pattern to determine the target VOC. Therefore, this concept replaced challenging and expensive laboratory experiments like the infrared or gas chromatographic analysis. Consequently, the selectivity and stability issues associated with the gas sensor element are improved by employing a sensor array. A portable e-nose is depicted in Figure 1.14.

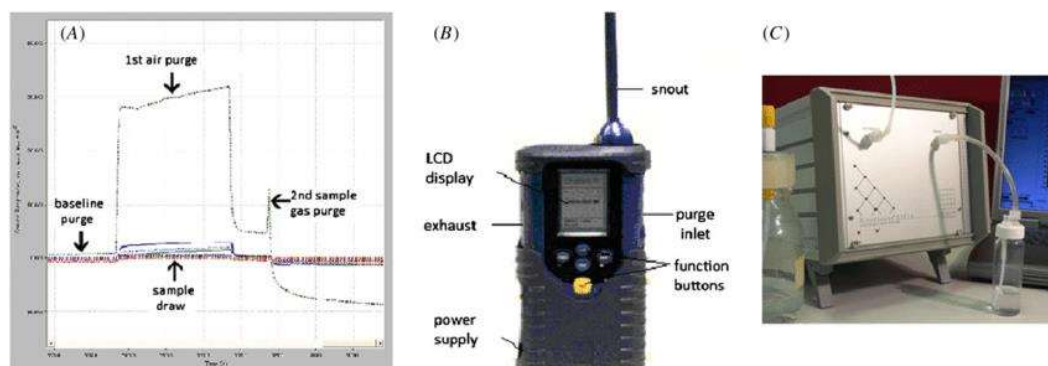


Figure 1.14 The portable e-nose (A) Typical response from Cyranose 320, (B) Conductometric sensor, and (C) Bloodhound Electronic Nose

1.3.3 Sensor Signal Pre-processing

To enhance the overall efficacy of the classifier, it can be desirable to pre-process the input data gathered from the sensor array before it is sent to the pattern analysis module. Pre-processing data in two stages may be beneficial for classifying and separating clusters more effectively. Initial raw data from the gas sensor array may contain noise, missing values, or inconsistent data. The system complexity and reaction time of the VOCs, gases and odors identification system may be diminished by pre-processing the raw data using an appropriate two-stage pre-processing method.

The generation of signatures for detecting different VOCs, gases, and odors uses non-selective sensor elements in arrays. Because they generate distinctive signatures of gases and odors, these sensor arrays have been used to improve classification accuracy. These raw signatures are often highly complicated, and in many situations, direct analysis of these signatures hasn't produced accurate classification results. Two-stage pre-processing of the data is thus necessary.

1.3.3.1 Analysis of Space Transformation

The two-stage data pre-processing transform the raw data into a new analytical space domain where the hidden characteristics become visible and improve in pattern recognition. Therefore, it published literature that the two-stage data pre-processing step is the foundation for most successful PARC analyses. Applying an appropriate data pre-processing method could significantly increase the classifier's accuracy. The primary goal of a pre-processing step is to carefully select several parameters that

describe the sensor array response since this decision might significantly impact how well the subsequent models in the pattern analysis system perform.

The positive effects of data pre-processing are several. One is to "dimensionally reduce" the redundant dataset to eliminate unnecessary data. Furthermore, extracting appropriate information (feature extraction) can strengthen the data analysis and reduce complexity. Additionally, by transforming the data, data pre-processing establishes an appropriate analysis space which helps achieve the desired set target. Data processing generally improves the classification of VOCs, gases and odors.

Although some general steps can be identified, pre-processing is somewhat dependent on the underlying sensor technology: (a) Baseline manipulation, (b) Normalization/standardisation, (c) Analysis of space transformation, (d) Classifiers.

To enhance contrast and drift correction, baseline manipulation requires altering the sensor response for its baseline. Three baseline modification techniques are commonly used: difference, relative, and fractional. To remove additive drift from the sensor response, implement the difference approach, which directly subtracts the baseline. Relative manipulation generates a response without dimensions by dividing by the baseline and eliminating multiplicative drift. Lastly, the fractional manipulation subtracting from and dividing by the baseline produces dimensionless and normalised responses. The block schematic of pre-processing using the space transformation method is depicted in Figure 1.15.

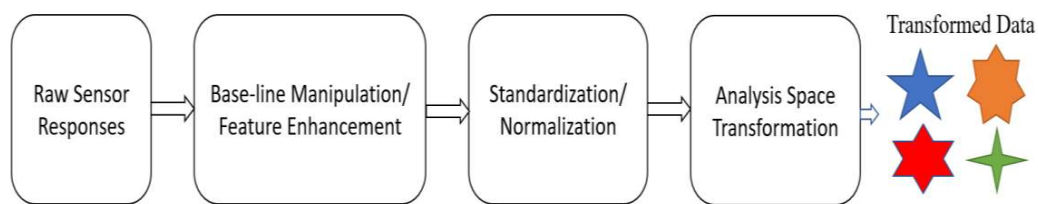


Figure 1.15 Block Schematic of Pre-processing using Space transformation method

The feature vector is generated for the subsequent pattern analysis modules during the normalizing/standardising operations.

Transform the sensor data from its original space to a new space that more accurately captures the underlying structure of the data through space transformation analysis. Rotation, translation, scaling, and projection are some methods used in space transformation analysis. A particular angle around an axis rotates the data. Data is translated when it is moved a specified distance in a particular direction. A data collection is scaled when its size has been modified consistently or irregularly. Data is mapped during projection from a higher- to a lower-dimensional space. The performance of machine learning models may be enhanced by using this method to identify hidden patterns and reduce the dimensionality of the data.

Principal component analysis (PCA), independent component analysis (ICA), kernel principal component analysis (KPCA), and linear discriminant analysis (LDA) are some of the techniques used for transforming the analysis space. The most critical information is preserved while the sensor data is transformed using a linear approach called PCA to generate a new space that optimizes variance and reduces dimensionality. Through partitioning sensor data into independent components depending on their statistical characteristics, ICA is a nonlinear technique that can identify hidden patterns and diminish the dimensionality of the data. Applications for space transformation analysis include robotics, machine learning, robotic graphics, image processing, and more.

Aishima has used PCA to distinguish between different alcoholic beverages using their smells [47] and Di Natale et al. gas sensor array and PCA to differentiate vintage of wine in the same category [48]. Rajput et al. have used the SPCA domain to classify and quantify four types of gases/odors [49]. Zhang et al. proposed kernel PCA-based LDA for sensor selection in an electronic nose [50]. Adib et al. used LDA to classify burning smells of cotton, beech and printed circuit board [51]. Xu et al. developed a hybrid gas identification and concentration measurement system using KNN classification after modelling nonlinear characteristics of binary mixtures of CO and CH₄ gas components using KPCA [52]. Olenevaa et al. developed a quick and straightforward analytical technique viz. LDA and SVM classification models to identify children's toys tainted with possibly harmful VOCs [53]. Zhang et al. used

PCA, LDA and BP-ANN for hydrogen and formaldehyde detection interference and got 93.35 % maximum classification accuracy [54].

There are following analysis space transformation techniques, which have been worked upon [47] – [54]:

- Principal Component Analysis (PCA)
- Linear Discriminant Analysis (LDA)
- Independent Component Analysis (ICA)
- Kernel Principal Component Analysis (KPCA)
- Quadrature Principal Component Analysis (QPCA)

1.3.3.2 Classifiers

This section provides an overview of the work accomplished to develop and deploy computational algorithms in general and pattern analysis methods in particular for classifying VOCs, gases, and odors. When exposed to multiple VOCs, gases, or odors, an array of gas sensors will generate a multivariate response with partly overlapping responses. This response may be used as an electronic fingerprint to classify an array of odors using pattern analysis methods. The revolutionary discoveries of Gardner represented the beginning of an era in which pattern analysis methods combined with sensor arrays to develop the e-nose [55], [8], [36]. Soft computational approaches have significantly reduced dependency on perfect and precisely developed sensor hardware, modernizing the field of artificial olfaction. By properly using soft computational approaches, it is feasible to significantly increase the discrimination acquired from the response of inadequately selective sensors, reducing expenditure on the potential need for replacement and the development of fresh sensor hardware. The artificial neural network (ANN) is a foundation of soft computing. They are a popular option for a broad range of computational tasks due to their tremendous learning capacity, massively parallel design, and accessibility of many learning algorithms for their training. Additionally, the primary viewpoint of this thesis illustrates the application of the best neural network architectures to classify VOCs, gases, and odors

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in real-time scenarios. The analysis of additional pattern recognition methods or classification algorithms in gas sensing is thus made clear as follows:

- Support Vector Machine (SVM)

Support Vector Machines (SVMs) have been widely applied to pattern classification problems and nonlinear regressions. SVM is a fast and dependable classification algorithm that performs very well with limited data to analyse. Much of the computation is spent on tuning two important parameters, i.e., γ and C . γ is the parameter related to the span of an RBF kernel: the smaller the value is, the wider the kernel spans. C controls the trade-off between the complexity of the SVM and the number of non-separable samples. A larger C usually leads to higher training accuracy. Huang et al. have developed an e-node using ten metal-oxide sensor arrays interfaced with an STM32 microcontroller for wine and oil tests. SVM and KNN classifiers have been used for classification and got 96.3% and 93.3% accuracy, respectively [56] - [59].

- K- nearest neighbors (KNN)

The supervised machine learning approach known as K-Nearest Neighbors (KNN) may use regression and classification applications. The method memorizes the training set and assigns the majority class label of the K-neighbors to the new data point. During prediction, the algorithm examines the training set for the K nearest (i.e., nearest) data points to the new data point. K is a hyperparameter whose value must be specified by the user. KNN issues with high-dimensional data or classes with imbalances may be computationally expensive, particularly for enormous databases [59].

- Naïve Bayes (NB)

NB is based on the Bayes theorem of probability theory and strongly assumes independence among the features. It is based on the Bayesian theorem, which states that the probability of an event occurring given some prior knowledge about the event is proportional to the likelihood of the event given prior knowledge [56], [61].

- Stochastic Gradient Descent (SGD)

The SGD approach adapts the model parameters iteratively according to the gradient of the loss function relative to the parameters. The gradient is calculated using a mini-batch of training samples randomly selected from each iteration's total dataset. The obtained gradient and a learning rate hyperparameter are then used to update the model parameters. The computational load of establishing the gradient is reduced, and convergence can be accelerated by using mini-batches rather than the complete dataset. However, the random sampling of the mini-batches introduces randomness into the gradient estimation, which can cause the optimization process to oscillate around the ideal solution [60].

- Logistic Regression (LR)

Logistic regression is a popular statistical technique for binary classification problems, aiming to predict a binary result (i.e., either 0 or 1) based on a collection of input characteristics. The logistic regression method calculates the probability of the binary result depending on the input characteristics using a logistic function. Any input value is transformed into a value between 0 and 1, representing the probability of the binary outcome by the logistic function, also called the sigmoid function [61].

- Recursive Discriminant Analysis (RDA)

The classification method known as recursive discriminant analysis (RDA) is predicated on the concept that the covariance matrices of each class are equal. RDA chooses the characteristic at each phase, minimising the within-class variation and increasing the variance across classes. Fisher's discriminant ratio for each feature is computed to do this, and the feature with the highest ratio is selected [57].

- Random Forest (RF)

Random Forest (RF) classifier combines the output of multiple decision trees to reach a single result. Its ease of use and flexibility have fuelled its adoption, as it handles classification and regression problems. RF is a supervised machine learning algorithm that builds decision trees on different samples and takes their majority vote for classification and average in case of regression. Random forest's main limitation is that

many trees can make the algorithm too slow and ineffective for real-time predictions. RF is fast to train but quite slow to create predictions once they are trained. Tam et al. have developed a system for the prevention of cooktop igniting using 14 sensors and used SVM, RF, and Decision Tree (DT) for the fires obtained by burning oils from canola, maize, olive, sunflower, and soy, achieving 96.9% accuracy using SVM to predict the pre-ignition situations [58], [61].

- Decision Tree (DT)

A decision tree classifier is a machine-learning algorithm for classification tasks. It is a tree-like model where each node represents a feature or attribute, and each branch represents a decision rule. The tree is constructed by recursively partitioning the data into subsets based on the most informative features until a stopping criterion is met, such as the purity of the subsets. The algorithm starts at the root node and evaluates the corresponding feature to classify a new instance. Based on the decision rule, it moves down the tree to the next node until it reaches a leaf node, representing a class label. In this case, the criterion used is "entropy," which measures the impurity of the nodes in the decision tree. Entropy measures the randomness of the target variable's distribution in a node, and the algorithm minimises it [58], [61].

- AdaBoost Classifier

The Adaboost algorithm is a boosting algorithm that combines multiple weak classifiers to form a strong classifier. The design of an Adaboost classifier involves selecting several hyperparameters, such as the number of estimators, learning rate, and random state, to optimise the model's performance. The number of estimators is the number of weak classifiers to combine to form a strong classifier. The learning rate is a hyperparameter that controls the contribution of each weak classifier to the final model.

- XGBoost Classifier

The design of an XGBoost classifier involves selecting several hyperparameters, such as the learning rate, number of estimators, maximum depth of the tree, minimum child weight, gamma, regularisation alpha, number of threads, and

cross-validation. The learning rate is a hyperparameter that controls the contribution of each tree to the final model. The number of estimators is the number of decision trees to create in the ensemble.

- **Multi-Layer Perceptron (MLP)**

The most popular kinds MLPs are feed-forward networks consisting of neurons. The input, hidden, and output layers are adjacent in feed-forward ANN models. Multiple neurons are present in each layer. MLP between the inputs and outputs creates a mapping function. During the learning process, the input neurons pass the training input data to the neurons in the hidden layer and forward it to the subsequent hidden and output layers. Each neuron's weighted inputs and bias in the hidden layer are used to perform mathematical computations. The proper activation function of each neuron is then used to map the cumulative response, and an output is obtained. Yang et al. have applied ANN to quantify hydrogen sulfide and nitrogen dioxide using a MOX gas sensor [62]. Lee et al. have used a thick-film gas sensor array with ANN to recognise explosive gases/odors [63]. Braun et al. have developed a gas sensor setup used by commercial metal-oxide-semiconductor (MOX) sensors, and another uses a commercial setup to collect disinfectant data. Further, they have classified these data by SVM and MLP and found 85%, and 87% accuracy, respectively [64].

1.3.4 Networks of E-Noses

A system is referred to as a cyber-physical system (CPS) when computing devices (cyber) are closely integrated and communicate with physical components (physical) to carry out certain activities or functions. CPS connects the physical world of sensors, actuators, and other devices with the digital world of computers and networks. The physical elements of a CPS may range from industrial equipment to automobiles to buildings to even human bodies, while the cyber elements are made up of computer software, communication networks, and computing systems. These two parts combine to create an integrated system that can perceive, analyze, and react to changes in the physical environment. This system allows communication, coordination, and control between the cyber and physical elements.

Technology, including sensors, actuators, embedded systems, wireless connectivity, the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML) are often used in CPS. These technologies allow data to be gathered from physical components, information to be sent, information to be analyzed and decisions to be made, and physical processes to be actuated. CPS is an integration of physical sensing: Gas/odor/VOCs sensing, networking: IoT/Cloud and computation: Pattern Recognition for classification. The description of components for cyber-physical systems is depicted in Figure 1.16.

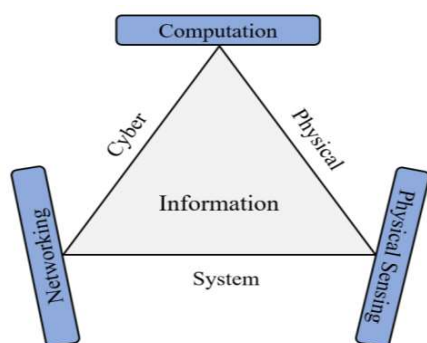


Figure 1.16 The description of Components for Cyber-physical System

1.4 Contextual Review of Previous Work

In recent literature, various approaches have been employed to classify gases and odors. Artificial Neural Network (ANN) classifiers have been used to classify certain gases/odors. In contrast, Rajput et al. have used the standardised principal component analysis (SPCA) domain to classify and quantify four different types of gases/odors, viz., acetone, carbon tetrachloride, ethyl methyl ketone and xylene. They have used a two-stage neural network system for performance enhancement [67]. Xu et al. and Olenevaa et al. have used ANN, Support Vector Machines (SVM) with Radial Basis Function (RBF) kernel, and Random Forest (RF) classification approaches [68], [53]. Rabeb et al. (2015) have described a laboratory-designed WO_3 gas sensor array to determine the fingerprints of gas samples. Ozone, ethanol, acetone, and a binary mixture of ozone and ethanol have been exposed on the sensor array at a constant temperature. Through PCA and SVM, they achieved well classification accuracy [70]. Andrew (2016) used a highly complicated hybrid model with the PCA-Probabilistic

Neural Network (PNN) method to diagnose incipient-stage fires in buildings using 1000 samples and three principal components [71]. Xu et al. (2018) developed a hybrid gas identification and concentration measurement system using K-Nearest Neighbour (KNN) classification after modelling nonlinear characteristics of binary mixtures of CO and CH₄ gas components using KPCA [72].

Furthermore, Zhao et al. (2016) developed a four-sensor array using neural networks to differentiate formaldehyde from three interfering VOCs (C₃H₆O, C₇H₈ and C₂H₅OH) using 108 gas samples. This work used the different variants of neural networks: the ELM with PCA and the BPNN with SVM. The PCA helps to increase the ELM's accuracy by pre-processing the sensor data, while the SVM approach yields the best accuracy [73]. Olenevaa et al. developed a quick and straightforward analytical technique to identify children's toys tainted with possibly harmful VOCs. They have used QCM based gas sensor array of eight sensor elements, each optimized for different sorbents, to classify toys into clean and dangerous ones with an accuracy of about 96%. This sensor array has been costly and uses complex versions of Linear Discriminant Analysis (LDA) and SVM classification models [8]. Unfortunately, they take much time and are disruptive when measuring samples. These devices are also very costly and enormous. Usually, literature represents only the study of various gases/odors produced in a particular paradigm. For example, in [74], the authors used an e-nose to monitor canned food's microbial spoilage. In [75], an e-nose has been implemented to detect LPG leakage. Moreover, gas sensor array-based e-nose has been used to detect milk spoilage [76]. In [77], the potential application of an e-nose to monitor food spoilage has been shown. Also, an e-nose has been successfully implemented for several food items [78].

The development of gas sensors uses materials like NiO, SnO₂, Fe₂O₃ and ZnO [79], which are common metal oxide semiconductor gas-detecting materials. MOS sensors have long-lasting life and short sensing response time, operated over elevated operating temperatures. MOS are inexpensive, solely sensitive to volatile gases and vapours, compact, and lightweight. Tin oxide, zinc oxide, titanium oxide, indium oxide, tungsten oxide, cerium oxide, copper oxide, and composite MOS for gases/odors detection are a few representative examples of the many metal oxide semiconductors.

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Metal Oxide gas sensors (MOX) are available at low cost, long lifetime, and fast response but relatively poor selectivity, performance drift, and background gas sensitivity.

In the context of fire detection, multiple sensors are used to capture the fire-linked signature patterns and analyse the same using various pattern recognition methods, sometimes by mimicking the human olfactory system, which is essentially an extended version of popular electronic noses (E-nose) [80]. E-noses have been popularly used to detect the presence and types of explosives, food and beverage quality assurance, process monitoring, cosmetics and fragrances, medical diagnostics and health monitoring, and automotive and aerospace applications.

Some popular gas sensors have been reported as semiconductor, catalytic bead, photoionization, infrared, electrochemical, optical, acoustic, gas chromatograph, calorimetric sensors, etc., [81]. Among these, semiconductor metal oxide gas sensors are highly-sensitivity, low-cost, and have a longer operational lifetime [81]-[82]. Wang et al. developed an ANN model to train their classification model. Three different ANN models, including backpropagation, RBF, and PNN, were used to train the fire classification model to detect the presence of a fire every time. The ANN models stated above can analyse multivariate data. However, they cannot categorise temporal patterns in sensor inputs [83]. D. Guttmacher et al. have performed experiments on fires of wood, cotton, foam, and alcohol under standardized (EN54) test fire scenarios and found that MOS sensors have faster response time [82]. Adib et al. have proposed an Electronic Nose as a fire detector. Linear Discriminant Analysis (LDA) was employed on a 16-element sensor array for the detection of cotton, beech, and printed circuit board (PCB) from their burning smells [84]. Wu et al. have created an E-Nose for qualitative and quantitative monitoring of five volatile, highly flammable liquids (ethanol, tetrahydrofuran, turpentine, lacquer thinner, and gasoline) using a 14-element Figaro metal-oxide sensor-based array with one digital temperature and humidity sensor interfaced with microcontroller; and used Principal Component Analysis (PCA) and ANNs for identification of the fire materials [85]. Tam et al. have developed a system for the prevention of cooktop igniting using 14 sensors and used SVM, RF, and Decision Tree (DT) for the fires obtained by burning oils from canola, maize, olive,

sunflower, and soy, achieving 96.9% accuracy using SVM to predict the pre-ignition situations [86]. Jaffe et al. studied wildfires through the spread of PM 2.5 and PM 10.0, which show a steep rise in their concentrations during the fire spread [87]. Findlay et al. used a single CO sensor and a PM sensor to identify wildfires before they started [88].

The literature review showed a growing interest in environmental monitoring using IoT and cloud-based technologies. Numerous environmental factors, including temperature, humidity, light, noise level, CO, and NO₂, were monitored indoors and outdoors on a university campus using an environmental monitoring system [89]. This system included the Raspberry Pi and MICS-4514 sensors. An IoT-based indoor environmental quality (IEQ) assessment system employing an Arduino Uno module and economical sensors like the DHT22 was developed in an experimental investigation [90]. An IoT-based measurement system with simple pressure, temperature, humidity, and gas sensors (BME680, DHT22, and MQ5) interfaced with an Arduino microcontroller has also been reported [91]. In a similar experiment, Kureshi et al. used temperature, humidity, a VOC sensor (BME680), and PM 2.5 and PM 10 sensors (SDS011) for air quality index (AQI) calculation. They used this information to increase awareness about indoor air pollution's hazards to human health [92]. Numerous gases, including CO₂, NO₂, ethanol, methane, and propane, were identified using the gas sensors MICS-6814 in an IoT-based system [93] developed for real-time IAQ monitoring.

An investigation of the emissions generated by different incense sticks and sparklers, including particles and benzene, was reported by Werner et al. [94]. Utilized indoors, they had a significantly unfavourable impact on the air quality. The indoor AQI was further explored using multiple low-cost PM sensors to effectively comply with the U.S. Environmental Protection Agency (EPA) [95]. The variation in the concentration ranges of CO, CO₂, total volatile organic compounds (TVOCs), and PM 2.5 over a period of 24 h was monitored in indoor environments by Capua et al., and a decision-making algorithm was used to manage the IAQ [96]. Rebecca et al. described the particles and gases released by burning Arabian incense and investigated the reactions of in vitro human lung cells to incense smoke [97]. A study on mosquito-

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repellent incense was conducted by Wang et al. The incense generated excessive gaseous and particle pollutants, as permitted under GB3095-2012 rules and the WHO advice [98]. Furthermore, the authors of [99] discussed green IoT for eco-friendly applications, and opportunistic routing (OR) was widely adopted in wireless sensor networks (WSNs) running asynchronous duty-cycled MAC protocols by the authors of [100].

The literature survey shows interest In Cyber-physical Systems (CPS) for different applications. Mois et al. have developed a CPS for environmental monitoring using Wi-Fi sensors and internet-of-things (IoT) platforms [141]. In their work, they have found that the outcomes of the experiments demonstrate that the suggested system is a practicable and simple method for environmental and ambient monitoring applications. Jarvinan et al. have developed and tested CPS system using low-cost sensors and microcontrollers for indoor and outdoor gas sensing [142]. In their work, they provide users with the ability to quickly prototype new gas sensor materials for testing in practical measurement circumstances. Nandy et al. have proposed a CPS framework for CO detection and control in residential and industrial environments [143]. In their work, they provide a brief overview of newly proposed optical-based CO detection methods is provided as well. Zhang et al. have developed building -CPS for building environment monitoring in real-time [144]. This work is an initial step towards CPS implementation in the Architecture, Engineering, Construction and Operation sectors, which allows an affordable use of available technologies, including IoT and machine learning to combine them with open building information modelling systems.

In the recent literature, researchers have only considered AQI and used specific sensors to detect and monitor a limited number of pollutant gases and PM concentrations to evaluate indoor air quality. The attention towards various VOCs, gases, and smokes in indoor environments is lacking. Furthermore, an electronic nose (e-nose) is a device that mimics the human olfactory system to identify and analyse various VOCs, gases, and smokes present in the environment. E-noses have been widely used for detecting and monitoring air pollution hazards, including industrial emissions, traffic emissions, and indoor air pollutants.

The proposed approach for pollution hazard detection and monitoring using e-noses is to provide real-time monitoring of airborne pollutants at a centrally located RDPS. The data collected at the RDPS are analysed by leveraging artificial intelligence-based algorithms and models to identify the classes of pollutants of interest. Pollution hazard detection networks are designed to detect, monitor, and predict the class and level of environmental pollution. Such networks can be categorized based on the sensors, spatial coverage, and data transmission methods. In addition, people worldwide utilize the Internet and GSM mobile-based networks, which require high power and paid subscriptions [101].

Further, the literature review shows a growing interest in disinfectant detection using IoT-based technology. Braun et al. have developed a gas sensor setup used by commercial tin-oxide-based Metal-Oxide-Semiconductor (MOX) sensors, and another uses a commercial setup to collect disinfectant data. Further, they have classified these data by Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) and found 85%, and 87% accuracy, respectively [102]. Chu et al. [103] have used five alcohol-based hand disinfectant samples in gel form. They found that 79% of respondents claimed skin problems, and 18% got eye discomfort when using these disinfectants. Zhang et al. [104] have developed a gas sensor array using six MOX sensor elements for carbon monoxide and methane with hydrogen and formaldehyde detection interference. Further, Different models were utilized and evaluated, including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Back Propagation- Artificial Neural Network (BP-ANN) PCA, LDA and BP-ANN and got 93.35 % maximum classification accuracy. Further, Jie et al. [105] have developed an E-Nose for daily indoor air quality monitoring in a living environment with BP neural network processing, comprising an embedded microprocessor, a gas sensors array, a low-power radio frequency chip, and a Wi-Fi module. Chowdhury et al. [106] have installed a Liquid stage sensor on the sanitizer station to monitor the sanitizer usage and the remaining level with Wi-Fi for data communication. Meydanci et al. [107] have developed RFID using Radio Frequency Identification (RFID) tags for monitoring hand cleaning behaviours with ZigBee for data communication from sensorised sanitizer stations for monitoring medical staff's compliance with hand hygiene. Nair et al. [108] have developed a low-cost non-contact hand sanitizer disinfecting system using

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dispenser's ultrasonic sensor, MLX90614 sensor, Arduino uno board, relay, servomotor, water reservoir, and hand sanitizer valve. In the recent literature, the researchers have only specific sensors to detect and monitor a limited number of VOC and Volatile Organic Compounds (VOCs), gases releases from different types of disinfectants used in the indoor environment. The attention towards various VOCs, gases and odors in disinfectant materials shows a research gap.

An electronic nose (e-nose) is a device that mimics the olfactory system of humans to identify and analyse various VOCs, gases and odors present in the indoor and outdoor environment [109]. E-noses have been widely used for detecting and monitoring household activity, health hazards, cleanliness, etc. Our method for disinfectant detection using e-noses is to provide real-time monitoring of VOCs, gases, and odors released from disinfectant at a centrally located remote data processing centre (RDPC) on the cloud network. The data collected at the RDPC is analysed by leveraging artificial intelligence-based algorithms and models to identify the classes of disinfectants [110]. The HP-IGSS for protocol-based disinfectant detection and monitoring system comprises a microcontroller and a gas sensor array of six cross-selective sensors connected to the cloud network as a gas sensor node and operates remotely in real time. Further, at the RDPC, we have used advanced two-stage analysis space transformation-based approaches to enhance the performance and efficacy of the proposed HP-IGSS using AWS cloud-based IoT platform, which can be operated worldwide, like in schools, hospitals, industries etc.

Further, the preponderance of breath biomarkers has been identified so far utilising spectrometry-based techniques, which are the industry standard exhaled breath analysis methods [115]-[116]. The most accurate method for identifying VOCs is gas chromatography (GC), Chromatography and Ion Mobility Spectroscopy (GC-IMS), Proton Transfer Reaction Mass Spectrometry (PTR-MS) and Selected Ion Flow Tube Mass Spectrometry (SIFT-MS) [111], [115]-[117] but these methods are complex, costly, time-consuming and require trained personnel. This high-end equipment uses statical methods for analyte analysis. Lekha et al. developed a non-invasive diabetic detection and classification technique with only two tin-oxide-based sensors (MQ 3 and MQ 5) and Convolutional Neural Network (CNN). In their experiment, they achieved

accurate detection and classification of type I and type II grades of diabetes using samples gathered from 25 volunteers by taking only two MQ sensors and AI models [112]-[114].

Invasive techniques can carry a higher risk of complications, such as bleeding, infection, and organ damage. It can also psychologically affect patients, such as anxiety, fear, or stress. Non-invasive techniques generally refer to medical techniques that do not require inserting instruments or other invasive procedures to examine a patient. This method is cost-effective and reduces the risk of complications and anxiety.

1.5 Definition of the Problems

Motivated by these researches in this thesis work, we have considered the following problems areas for contributions:

Problem statement I: Development of a high-performance electronic nose for real-time detection and monitoring of harmful compounds and odors in smart homes.

Such a system may be useful for real-time classification of VOCs/gases/odors that are usually generated in the household sector during daily chores and activities (e.g., worship, safety & security, hygiene, LPG leakage detection, cooking and smoking). This system can be used for the detection of various activities carried out by house residents. Our approach is based on two-stage modular processing architecture for real-time detection of various gases/VOCs/odors and achieve high performance.

Problem statement II: Development of an intelligent decision support system for generating real-time map of classes of fire during a fire hazard.

In this work, we proposed to develop an intelligent decision support system (IDSS) to generate a real-time ‘fire-map’ of such storage and distribution centres (SDCs) during a fire hazard and generate a real-time map of classes of fire, which the firefighters may use to mitigate the fire more efficiently by using right kind of fire extinguishers.

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To the best of the author's knowledge, it is the first time when all six classes of fire have been considered for generating a real-time map of 'classes of fire' for fire-fighting applications by using an IDSS.

Problem statement III: Development of a CPS using a LoRa-based networked intelligent gas sensor system (N-IGSS) for airborne pollution hazards detection and monitoring.

Under this, we intend to develop a CPS-based low-cost IoT-enabled N-IGSS for centralised data collection and analytics across large buildings and houses for real-time pollution hazard detection using a LoRa-based IoT network.

Problem statement IV: Development of an IoT-enabled intelligent gas sensor system (IoT-IGSS), another kind of CPS for real-time detection and monitoring of VOCs released from household disinfectants in real-time.

In this work, we proposed an IoT-enabled IGSS which can detect and monitor different types of VOCs released by the considered disinfectant materials when they are put to use in daily activity in the household environment, which is another kind of simpler CPS.

Problem statement V: Development of a cloud-based intelligent gas sensor system (IGSS), a CPS, for qualitative estimation of blood glucose level (BGL) through analysis of VOCs present in human breath.

In this work, we proposed to create a simpler CPS, a cloud-based IGSS network for possible qualitative estimation of BGL (viz. high, low and normal) through the VOCs present in the exhaled human breath for use in real-time.