Chapter 6

IoT-IGSS: Real-Time Detection of VOCs in Household Disinfectants using IoT-enabled Intelligent Gas Sensor System

In this work, we propose IoT-enabled High-Performance Intelligent Gas Sensor System (HP-IGSS) for detecting and monitoring Volatile-Organic Compounds (VOCs)/gases/odors released from different disinfectants as used in household environments. We interface six tin-oxide-based metal-oxide semiconductor (MOX) gas sensor elements with a microcontroller to capture real-time signature patterns of VOCs/gases/odors released by the considered disinfectant materials when they are put in use. The microcontroller sends the gas sensor responses to the cloud, from where data is ported to a Remote Data Processing Centre (RDPC) for further analysis for its use in the real-time scenario. In this experiment, six different types of disinfectant materials viz hydrogen-peroxide (used for surface-cleaning, cleaning cuts, hair dye, etc.), sanitizer and alcohol (used for hand-cleaning), phenyl, acid, and harpic (used for floor and bathroom cleaning) are used, and a dataset consisting of 900 samples were captured. These sensor array responses are pre-processed using the two-stage analysis space transformation method, i.e., Quantile Principal Component Analysis (QPCA) is used at the first stage. Subsequently, Naïve Bayes (NB), Random Forest (RF) and Support Vector Machine (SVM) classifiers are used at the second stage of processing. The proposed HP-IGSS test uses 30 unknown VOCs/gases/odors samples not used during the training and validation process. Experimentally, the SVM classifier train in the QPCA transformed dataset could classify all 30 test samples with 100% accuracy. The lowest Mean Squared Error (MSE) achieve 2.46×10^{-6}.

6.1 Introduction

In this digital world, every device is networked to one another. When these devices are interconnected to one another through the Internet, the Internet makes the devices smart. The Internet-of-Things (IoT) is a massive network of networked gadgets that store and gather information about their physical surroundings. As a result, the IoT is characterized as an ecosystem of connected things. Integrating IoT-powered devices and sensors has revolutionized healthcare facilities and systems. It has revolutionized people's lives by gathering and analyzing data for monitoring various processes and has significantly improved healthcare activities.

The SARS-CoV-2 or COVID-19 pandemic outbreak in 2020 has transformed the routine life of people all across the globe by changing the priorities of public healthcare and re-establishing the requirements for maintaining cleanliness [179]. Human employees presently perform disinfection work in contaminated locations (such as hospitals, homes, gymkhana, swimming pools, and quarantine halls). This raises the risk of exposure to highly infectious viruses, especially when suitable protective equipment is not used properly. In addition, human workers cannot ensure consistency in the disinfection quality. Chemical disinfection generally uses chlorine dioxide, ethanol, and hydrogen peroxide as the primary disinfectant [180]. It is essential to choose the appropriate disinfection strategy to prohibit the virus from spreading indoors while maintaining relatively low levels of byproducts in the air. To curb the viruses, it's crucial to maintain the spaces clean and sanitized and well-disinfected. Before rendering the area accessible to the public, IoT-based devices can be employed to identify and monitor the public spaces. An intelligent sensor system can hence be designed to ensure compliance with the prescribed protocols by connecting the ‘things’ across the globe for further information sharing [181].

The literature review shows that there is 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 6 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 [149]. 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, which is comprised of an embedded microprocessor, gas sensors array, a low-power radio frequency chip, and 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 behaviors with ZigBee for data communication from sensorized 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 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 [4]. 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 VOC, gases, and odors released from disinfectant at a centrally located remote data processing centre (RDPC) 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 [16].

This work introduces an CPS suitable HP-IGSS protocol-based disinfectant detection and monitoring system, which comprises of a microcontroller and a gas sensor array of six cross-selective sensors connected on the cloud network as a gas sensor node and operates remotely in real-time and monitoring system. 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. The architecture of CPS suitable HP-IGSS protocol-based disinfectant detection in Figure 6.1.

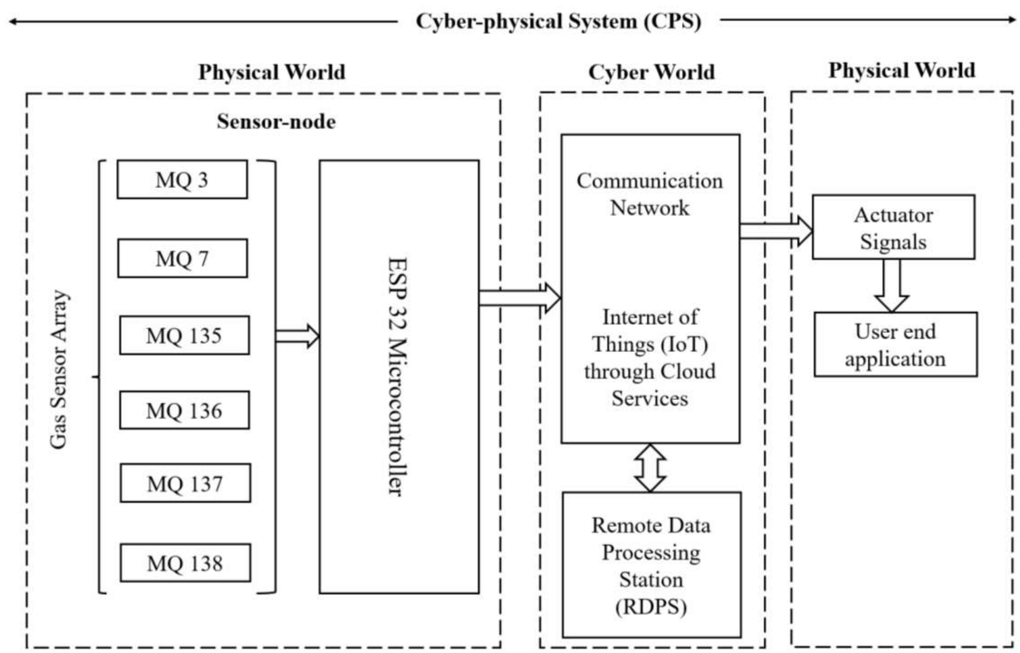

Figure 6.1 The architecture of CPS suitable HP-IGSS protocol-based disinfectant detection

In this experiment, we have considered six types of disinfectant materials viz hydrogen-peroxide (used for surface-cleaning, cleaning cuts, hair dye, etc.), sanitizer and alcohol (used for hand-cleaning), phenyl, acid, and harpic (used for floor and bathroom cleaning) to capture signature patterns of the VOCs, gases and odors released by them, respectively. The sensor node of the HP-IGSS is placed in a room where these disinfectants are applied at different times, and respective sensor node responses are uploaded on the AWS cloud from where this dataset is downloaded for further analysis and predictions at the RDPC for real-time analytics. At the RDPC, the dataset is transformed into a QPCA analysis domain and three classifiers viz. NB, RF and SVM are designed using the QPCA-transformed dataset for suitable classification, detection and monitoring [14], [22]. The basic schematic block diagram of the HP-IGSS is presented in Figure 6.2.

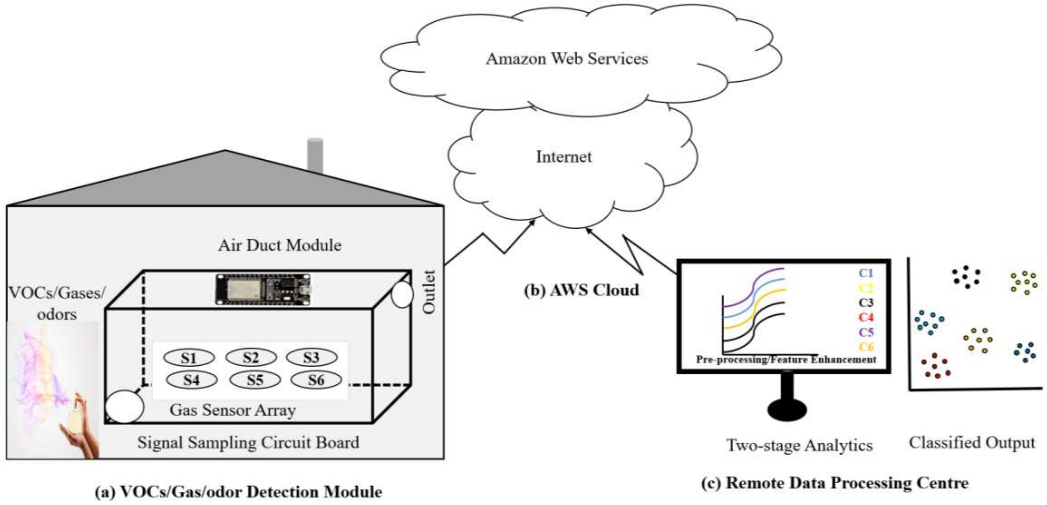

Figure 6.2 Block Schematic diagram of the High-Performance Intelligent Gas Sensor System (HP-IGSS)

6.1.1 Motivations and Contribution

The proposed system for detecting and monitoring VOCs, gases, and odours in household disinfectants is motivated by the need to improve the safety and health of individuals. Household disinfectants are commonly used to kill germs and bacteria but can also emit harmful chemicals that can cause adverse health effects. Therefore, there is a critical need for a reliable and accurate system that can detect and alert individuals to potential health hazards in real-time.

The proposed gas sensor system has numerous applications, including home and office environments, hospitals, schools, and other public places where disinfectants are commonly used. By providing accurate and real-time monitoring of VOCs/gases/odours released from different disinfectant materials, the proposed system can help individuals make informed decisions about their health and well-being. Moreover, the proposed system can contribute to environmental sustainability by reducing harmful chemicals in disinfectant materials and identifying safer alternatives. The utilities of this work are highlighted as follows:

1. A HP-IGSS is proposed for real-time detection and monitoring of disinfectant materials indoors (houses/schools/offices etc.).

2. For the first time, a cloud-connected protocol is used for real-time networked operations of e-noses for disinfectant detection.

3. The proposed HP-IGSS uses a two-stage analysis space transformation method to ensure the classifier models deliver high performance.

6.2 Materials and Methods

We have tested our proposed work by designing and fabricating the IoT-enabled HP-IGSS, as shown in Figure 6.2. Further details of HP-IGSS in the following sections have been provided:

6.2.1 The Design Concept of HP-IGSS

In this work, we have proposed an IoT-enabled HP-IGSS using a three-step approach. In the first step, we generated the signature patterns from disinfectant materials using six Tin-oxide based MOX gas sensors (MQ 3, MQ 7, MQ 135, MQ 136, MQ 137, and MQ 138). All these sensor elements are cross-selective and respond to multiple VOCs/gases/odors with different sensitivities [4]. The second step sends the gas sensor node responses to the cloud platform. Amazon Web Services (AWS). A cloud offers various services like computation, storage, databases, application deployment, blockchain, robotics, AI platforms, and IoT. AWS IoT Core also supports secure connection and managing many devices at scale. The data has been stored in the cloud using the DynamoDB table and RazorSQL and downloaded at the RDPC. Further, in the third step, we used a two-stage analysis space transformation method to transform the captured dataset into the transformation domain using QPCA [49]. In the second stage of the third step, we used SVM, NB and RF to efficiently classify the transformed dataset. The proposed HP-IGSS comprises three sections, as shown in Figure 6.3 (a) – (c).

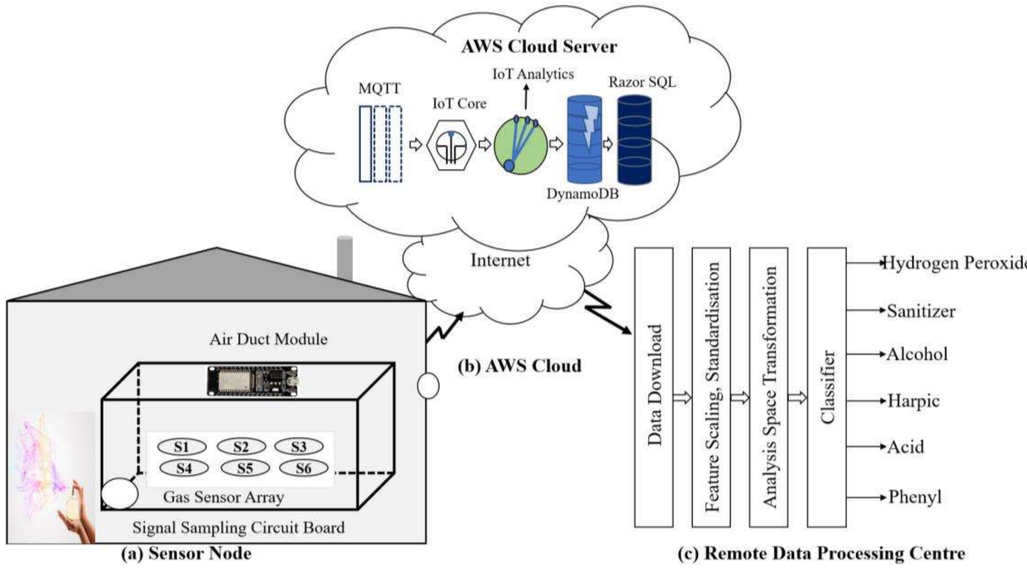

Figure 6.3 (a) – (c) The proposed architecture of an HP-IGSS

In this work, we have used six different types of tin-oxide-based gas sensors, as shown in Table 6.1, interfaces with a microcontroller (ESP32) to create the VOCs/gases/odor signature response generation module. A 5V DC power supply powers these sensors. The proposed approach is planned for detecting different types of disinfectants in real-time. The captured raw sensor responses are analysed remotely in the analysis transformation space using the QPCA transformation method. All the six clusters belonging to the considered disinfectants viz, hydrogen-peroxide, sanitizer, alcohol, harpic, acid, and phenyl classes are formed with good inter-cluster separation.

Table 6.1 Description of Gas Sensor Characteristics

S.No.	Components	Detectors	Range (PPM)
1	MQ 3	Alcohol, Ethanol, smoke	25 – 500
2	MQ 7	CO	10 – 500
3	MQ 135	CO, Ammonia, Alcohol, smoke	10 – 1000
4	MQ 136	Hydrogen Sulfide	1 – 200
5	MQ 137	Ammonia	5 – 500
6	MQ 138	Benzene, toluene, Acetone, propane	5 - 500

6.2.2 The Prototype designs

The prototype includes a six-element tin-oxide metal-oxide- ~~(~~MOX~~)~~ based gas sensor array, which generates real-time signature patterns of the disinfectants and sends them to the cloud. All the sensors are fitted on the breadboard, and wire connections are made with the microcontroller. The electrical characteristics of various sensors and devices used in this HP-IGSS are shown in Table 6.2.

Table 6.2 Electrical Characteristics of Components

S.No.	Components	Input Voltage	Power Ratings
1	ESP32	5V	130mA
2	ESP32 GPIO pins	3.3V	40mA
3	MQ Sensors × 6	5V	150mA

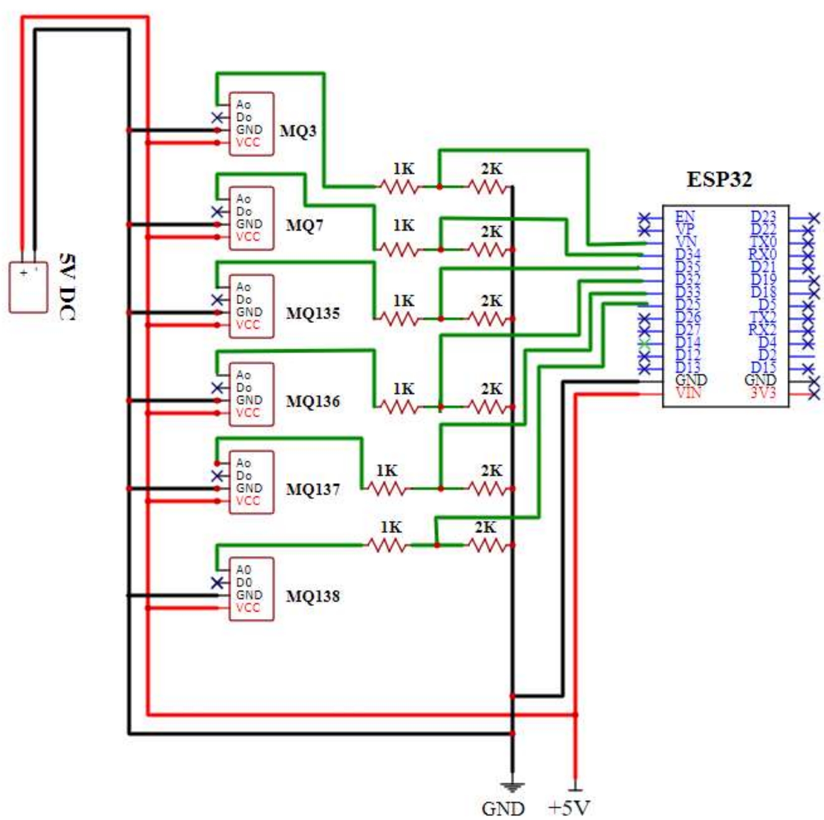

Figure 6.4 Basic Circuit Diagram of HP-IGSS

All experiments were conducted in a closed room (12 × 10 × 11 feet). In this experiment, we used six different types of materials. These are hydrogen peroxide (surface-cleaning, cleaning cuts, hair dye, etc.), sanitizer and alcohol (hand-cleaning), phenyl, acid, and harpic (floor and bathroom cleaning). Six tin-oxides MOX based gas sensors are integrated as a portable gas sensor array and put in the experiment room to gather sensor responses. The physical view of fabricated HP-IGSS for disinfectant detection and monitoring is shown in Figure 6.5.

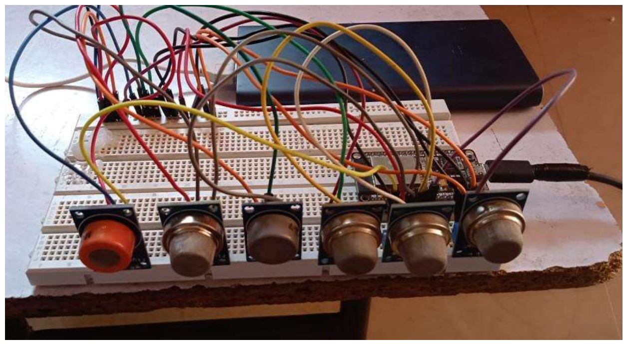

Figure 6.5 Physical Prototype of HP-IGSS

6.2.3 The Experimental Details

We conducted our experiments in an indoor environment. We deployed the HP-IGSS sensor node at a fixed table (height = 1 foot) to capture real-time sensor responses. Initially, the gas sensor system is purged with the ambient air to obtain the baseline signature pattern under steady-state conditions of the sensor array responses for fifteen minutes. Once the sensor array responses become steady, the array is exposed to one of the considered classes of materials to release respective VOCs, gases and odors for ten minutes at a rate of 15 samples per minute. After ten minutes of exposure, the gas sensor array is purged with ambient air until the sensor responses return to the baseline signature patterns. This process is repeated for each of the considered classes of VOCs, gases and odor, and the raw sensor array response dataset is captured in its totality. Accordingly, each experimental phase continues for 55 minutes, and raw sensor responses have been captured. During this experimental period, 900 samples (150 samples × 6) were captured at the sampling rate of 15 samples per minute. In this dataset, 870 samples (145 samples × 6) were for training, and 30 samples (5 samples × 6) were for testing. All 30 samples of the testing dataset have not been used for training and validation purposes. The experiment details have been given in Table 6.3.

Table 6.3 Distribution of Disinfectant Details

Experimental Materials	Total Samples	Training Samples	Testing Samples	Class
Hydrogen-peroxide	150	145	5	1
Sanitizer	150	145	5	2
Alcohol	150	145	5	3
Harpic	150	145	5	4
Acid	150	145	5	5
Phenyl	150	145	5	6
Total	900	870	30	

6.2.4 Contextual Background of Analysis Space Transformation Method

We have utilized the analysis space transformation method to transform the raw dataset into the analysis space where the clusters of various classes of materials show distinct clusters leading to the better classification performance of the HP-IGSS. These captured disinfectants dataset have been pre-processed by the analysis space transformation method by using QPCA [49],[148]-[149].

6.2.4.1 Data Pre-processing

The proposed work has been based on performance enhancement using the QPCA analysis space transformation approach. It has been shown that analysis space transformed data clusters with better inter-cluster separation. An illustrative diagram of the analysis space transformation process has been shown in Figure 6.6.

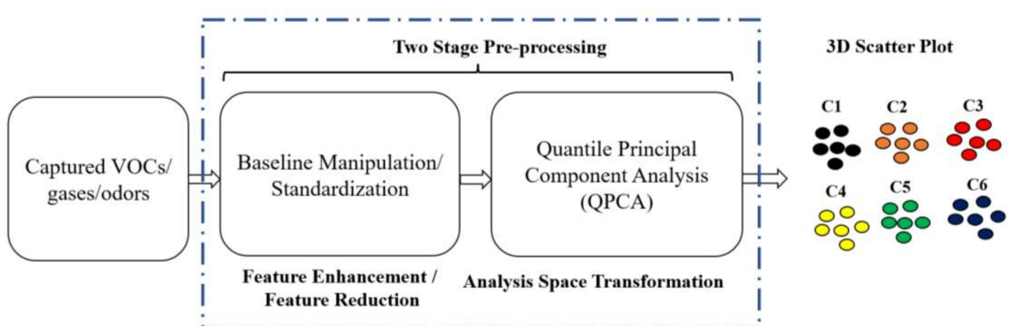

Figure 6.6 Block Schematic Diagram for 3D Scatter Plot

In this experiment, we have pre-processed the raw sensor responses using QPCA. It is a statistical technique that is used for dimensionality reduction and feature enhancement methods [49], [148]-[149]. It transformed the captured raw data into the analysis space transformation domain for precise and compact visualization in a separate class of disinfectants. The first three principal components (PCs) contain 86.74% information we used for the 3-D scatter plot, as shown in Figure 6.7.

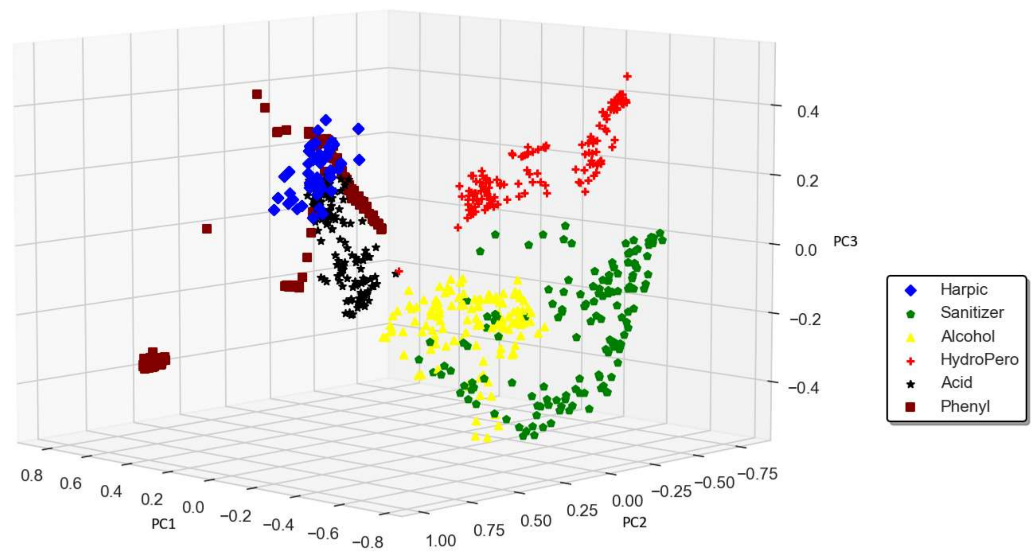

Figure 6.7 3D Scatter Plot QPCA transformed data.

6.2.4.2 Design of the Classifiers

Accordingly, the raw sensor responses were first transformed into the analysis space domain, i.e., in the QPCA domain. QPCA is a very effective method, popularly used for feature extraction and dimensionality reduction [49], [149]. For the performance enhancement of the HP-IGSS, we have used QPCA as the method for feature enhancement. We have all the PCs for the training and testing the classifier used in the HP-IGSS without any information loss.

The transformed dataset consists of 900 samples, with each sample vector comprising six elements. The transformed dataset was then segregated into two parts, i.e., the training and testing dataset consisting of 870 and 30 samples in the QPCA transformed domain, respectively. Further, we deployed the NB, RF and SVM machine learning models and evaluated their performance [64], [102]. To minimize variation, RF develops a large number of decision trees. RF solves both classification and regression problems. The final prediction depends on the majority voting of the tree results, and RF implements a bagging approach to obtain results. It uses a bootstrap data set and a random selection of characteristics to avoid overfitting and variance. The process flow of the proposed has been shown in Figure 6.8.

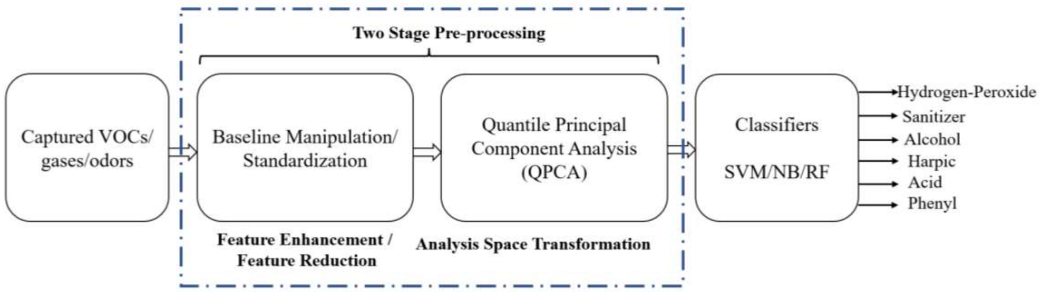

Figure 6.8 Block Schematic Diagram of the Proposed HP-IGSS

We have implemented three classifiers NB, RF and SVM classifier. In this experiment, RF and NB are less performers, whereas SVM has classified all separate classes with 100% accurate classification, as shown in Figure 6.11.

RF: RF is a type of decision tree algorithm that combines multiple decision trees to create a more accurate and stable model. Each decision tree is trained on a random subset of the data and a random subset of the features. Each decision tree in the RF is trained independently and makes a prediction based on the majority vote of all the trees. The RF classifier model is shown in Figure 6.9.

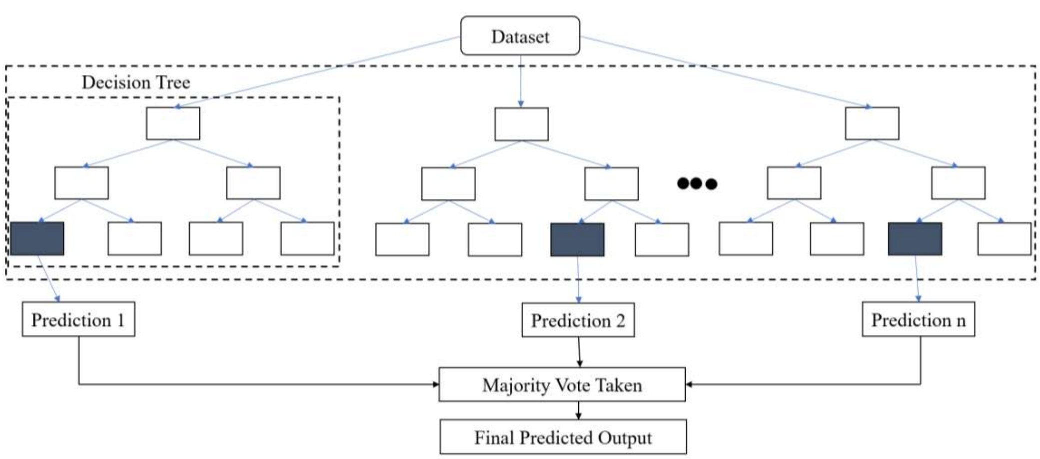

Figure 6.9 RF classifier Model

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.

Let X is an unseen data sample whose class label is unknown, and C is the class that X belongs to class C.

P(C): Prior probability, P(X): probability that X is observed.

P(X|C): likelihood, probability of observing sample X given that H holds.

P(C|X): posterior probability, the probability of H holds given X is observed.

$$P(A|B) = \{P(B|A) \times P(A)\}/P(A) \tag{56}$$

$$P(C|X) = \{P(X|C) \times P(C)\}/P(X) \tag{57}$$

$$P(C|X) = P(X|C) \times P(C) \tag{58}$$

SVM: SVM is a supervised learning algorithm that separates data points into different classes by finding the best possible boundary or hyperplane. SVM finds the best possible hyperplane or boundary that separates the data points into different classes. The goal is to maximize the distance between the boundary and the closest data points of each class, which are called support vectors. The distance between the separating hyperplane and the closest support vectors is called the margin. SVM aims to maximize the margin to increase the robustness of the model to new data points. The SVM algorithm has two important parameters, C and gamma. The C parameter controls the trade-off between maximizing the margin and minimizing the classification error. The gamma parameter controls the shape of the decision boundary. The SVM model is depicted in Figure 6.10.

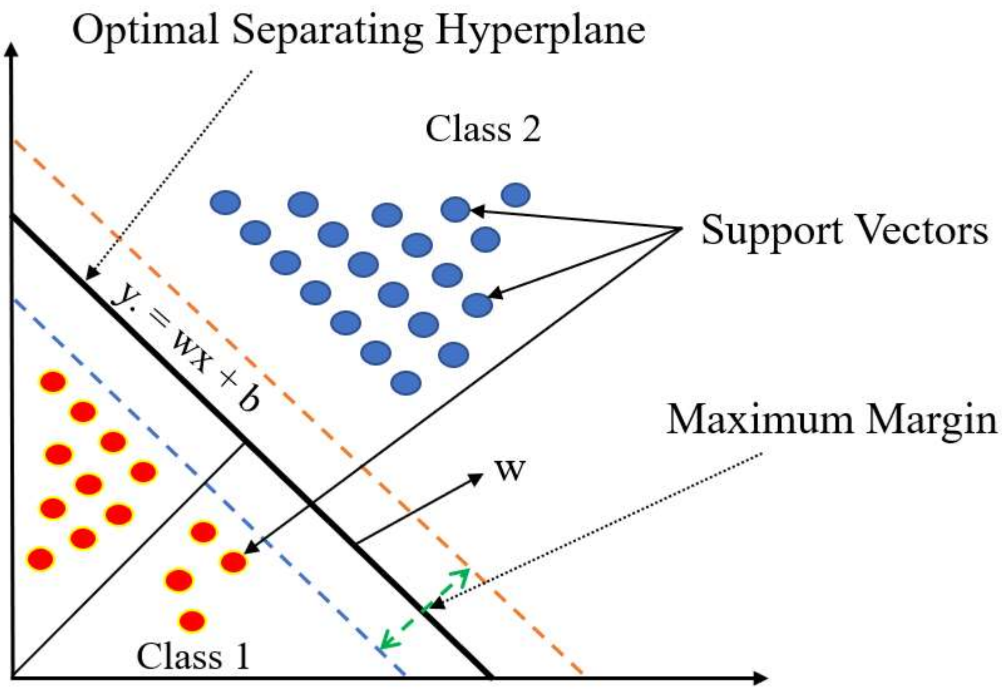

Figure 6.10 Classification architecture of SVM

6.3 Results and Discussions

In this experiment, the raw gas sensor array responses have been first transformed into the QPCA transformation space, and three classifiers viz. NB, RF, and SVM have been designed and tested in the QPCA domain itself. The RF trained using QPCA transformed data achieved the 'all correct' classification accuracy over the 30 test samples taken from the six disinfectant types releasing distinct VOCs, gases and odors. The proposed HP-IGSS has been aimed at being portable, easy to use and affordable in real-time scenarios. Further, the classification performance of the HP-IGSS trained and tested in the QPCA domain and by using the responses of the gas sensor array using 30 unknown samples has been shown in Figure 6.11.

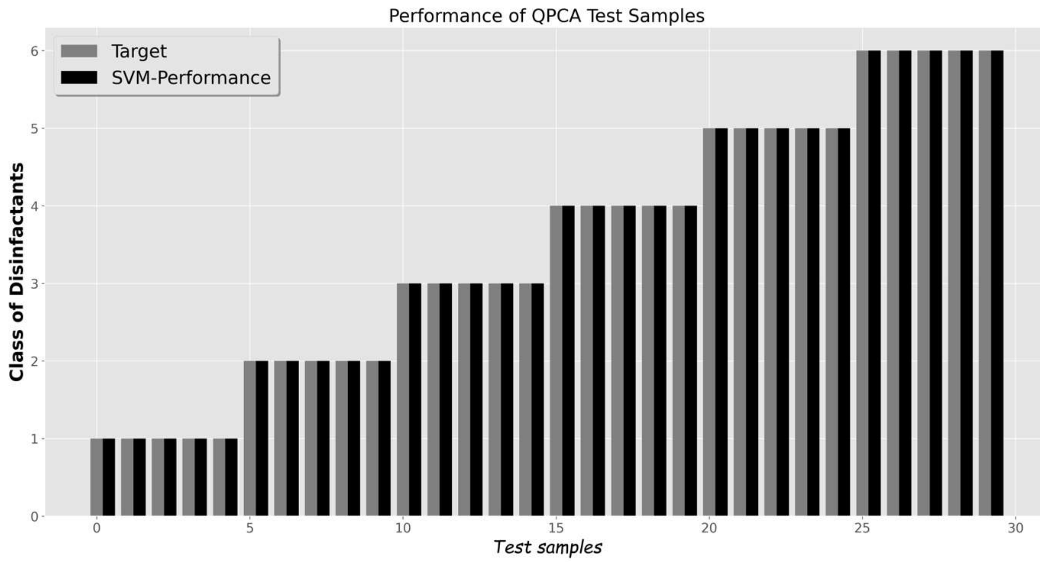

Figure 6.11 Classification Performance of the HP-IGSS designed in the QPCA transformed data.

For the sake of further clarity, the confusion matrix of the classification performance of the SVM classifier has been shown in Figure 6.12, which shows 'all correct' classification of the considered 30 unknown samples taken from the testing dataset, not used for training the classifier models in QPCA transformation domain.

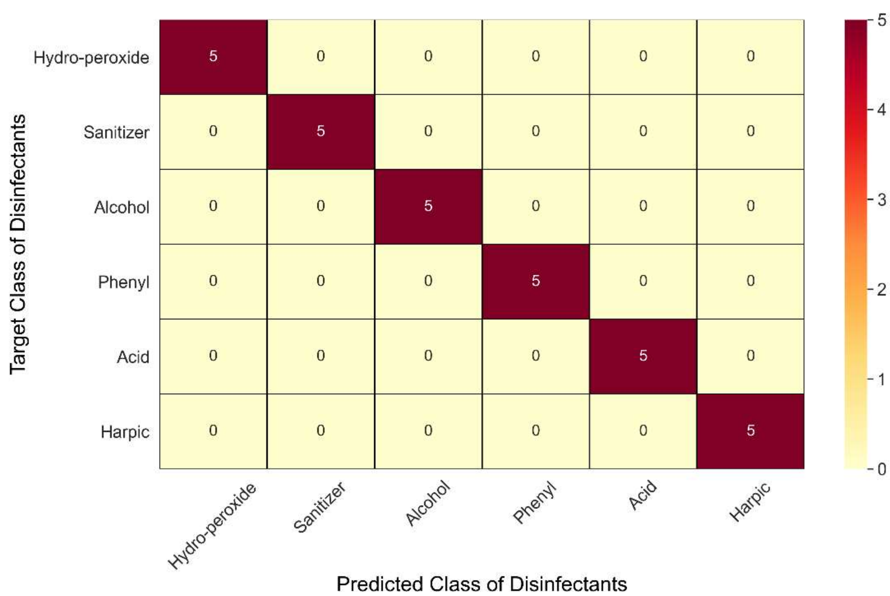

Figure 6.12 Confusion Matrix of SVM Classifier

Moreover, the efficacy of obtained results has also been shown using confusion matrix-based parameters such as accuracy, precision, recall, and F1-score determined using True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) scores. The following equations are used to calculate these parameters.

$$Accuracy = \frac{\mathrm{TN + TP}}{\mathrm{N}} \tag{59}$$

$$Precision = \frac{TP}{TP + FP} \times 100 \tag{60}$$

$$Recall \ = \frac{TP}{TP + FN} \times 100 \tag{61}$$

$$F1\_score \ = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{62}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{63}$$

$$Specificity = \frac{TN}{FP+TN} \tag{64}$$

$$G_{mean} = \sqrt{(\frac{TP}{TP+FN})(\frac{TN}{FP+TN})} \tag{65}$$

Where N = total number of samples

Further, we have calculated the MSE, root mean squared error (RMSE), mean absolute error (MAE), relative root mean squared error (RRMSE), mean bias error (MBE), and root mean squared logarithmic error (RMSLE) to evaluate of the regression model.

MBE is the average difference between the predicted values and the actual values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2 \tag{66}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{67}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}| \tag{68}$$

$$RRMSE = \sqrt{\frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(\hat{y_i})^2}} \tag{69}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i}) \tag{70}$$

$$RMSLE = \sqrt{(log(y_i + 1) - log(y_i^{\wedge} + 1))^2} \tag{71}$$

Where, y_i = actual sample, $y_i^{\wedge}$ = predicted sample and n = number of samples

Further, RF and NB classifiers have achieved 90% and 93.33% classification accuracy, respectively, for the 30 unknown test samples. On the other hand, the SVM classifier achieved 100% classification accuracy for all 30 test samples, as considered. While classifying the considered VOCs, gases and odors, we have compared the prediction error for each test sample. The error ranges between 2.46×10^{-6} to 2.65×10^{-4}, with an average MSE of 6.18×10^{-5} for 30 unknown test samples. The classification performance of the considered best-trained classifier is shown in Table 6.5.

Table 6.4 Accuracy Performance of QPCA transformed data of different classifier.

Classifiers	Accuracy (%)
RF	90
NB	93.33
SVM	100

The MSE ranges between 3.26×10^{-3} to 9.70×10^{-1}, with an average of 3.26×10^{-1} of raw data. The RMSE ranges between 1.57×10^{-3} to 1.63×10^{-2}, with an average of 5.99×10^{-3}, the MAE ranges between 1.15×10^{-3} to 8.43×10^{-3}, with an average of 3.5×10^{-3}, RRMSE ranges between 5.06×10^{-4} to 2.03×10^{-3}, with an average of 1.19×10^{-3}, MBE ranges between 6.13×10^{-5} to 1.67×10^{-3}, with an average of 7.8×10^{-4}, RMSLE ranges between 6.07×10^{-4} to 2.37×10^{-3}, with an average of 1.66×10^{-3}, for 30 unknown test samples. Regression performance of QPCA transformed dataset is presented in Table 6.5.

Table 6.5 Regression Performance of QPCA transformed data

Class	MSE of Raw data	Proposed Method					
		MSE	RMSE	MAE	RRMSE	MBE	RMSLE
Hydrogen-peroxide	3.26×10^{-3}	7.29×10^{-6}	2.69×10^{-3}	2.10×10^{-3}	1.16×10^{-3}	6.82×10^{-5}	2.32×10^{-3}
Sanitizer	1.04×10^{-2}	1.00×10^{-5}	3.17×10^{-3}	1.91×10^{-3}	1.15×10^{-3}	7.73×10^{-4}	1.72×10^{-3}
Alcohol	9.70×10^{-1}	7.24×10^{-5}	8.51×10^{-3}	4.79×10^{-3}	1.19×10^{-3}	5.65×10^{-4}	1.59×10^{-3}
Harpic	4.41×10^{-2}	1.39×10^{-5}	3.73×10^{-3}	2.60×10^{-3}	1.08×10^{-3}	1.67×10^{-3}	1.35×10^{-3}
Acid	9.22×10^{-3}	2.46×10^{-6}	1.56×10^{-3}	1.15×10^{-3}	5.05×10^{-4}	6.13×10^{-5}	6.07×10^{-4}
Phenyl	9.17×10^{-1}	2.64×10^{-4}	1.62×10^{-2}	8.43×10^{-2}	2.23×10^{-3}	1.53×10^{-3}	2.37×10^{-3}
Min	3.26×10^{-3}	2.46×10^{-6}	1.56×10^{-3}	1.15×10^{-3}	5.05×10^{-4}	6.13×10^{-5}	6.07×10^{-4}
Max	9.70×10^{-1}	2.64×10^{-4}	1.62×10^{-2}	8.43×10^{-2}	2.23×10^{-3}	1.67×10^{-3}	2.37×10^{-3}

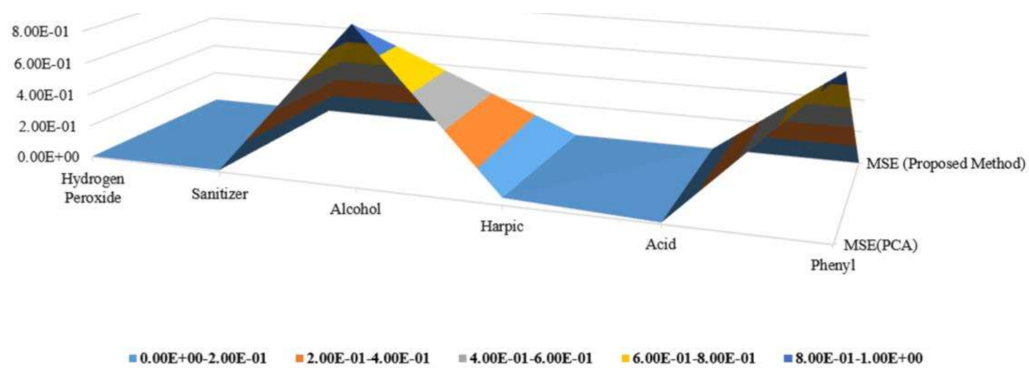

Figure 6.13 MSE Performance of QPCA Transformed Data

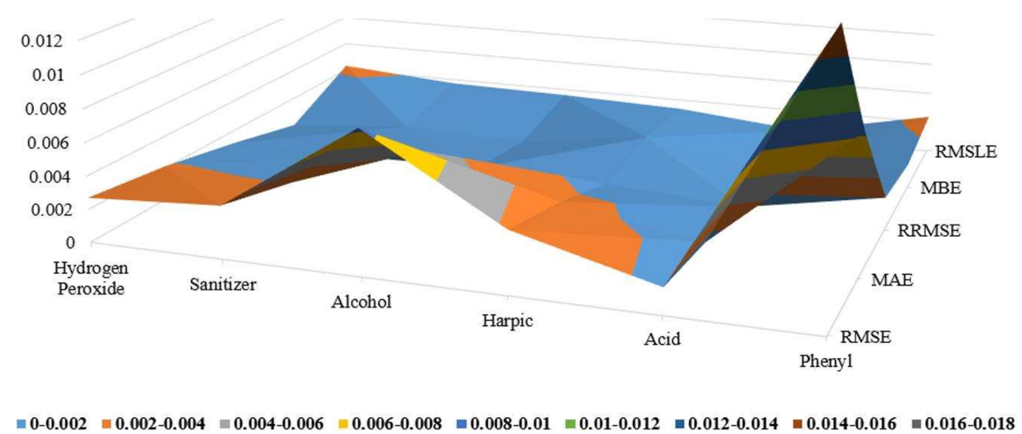

Figure 6.14 Regression Performance of QPCA Transformed Data

Further, Figure 6.15 shows performance of the accuracy, precision, recall, F1-score, sensitivity, specificity and G-mean of RF, NB and SVM. We have observed that

SVM is best performer than NB and RF in respect with all parameters. Classification accuracy of RF and NB are 90%, 93.33%, respectively where SVM got 100%.

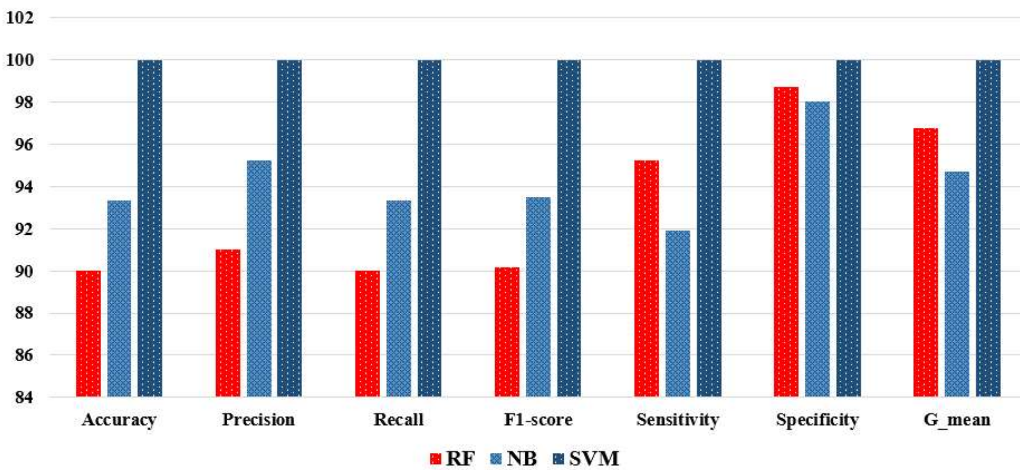

Figure 6.15 Performance of RF, NB and SVM Classifiers