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Toxic Gases Detection and Tolerance Level Classification Using Machine Learning Algorithms

S. Deepan, and M. Saravanan

***Abstract*—with rapid population increases, people are facing the challenge to maintain healthy conditions. One of the challenges is air pollution. Due to industrial development and vehicle usage air pollution is becoming a high threat to human life. This air pollution forms through various toxic contaminants. This toxic contamination levels increase and cause severe damage to the living things in the environment. To identify the toxic level present in the polluted air various methods were proposed by the authors, But failed to detect the tolerance level of toxic gases. This article discusses the methods to detect toxic gasses and classify the tolerance level of gasses present in polluted air. Various sensors and different algorithms are used for classifying the tolerance level. For this purpose "Artificial Sensing Methodology" (ASM), commonly known as e-nose, is a technique for detecting harmful gases. SO2-D4, NO2-D4, MQ-135, MQ136, MQ-7, and other sensors are used in artificial sensing methods (e-nose). "Carbon monoxide, Sulfur dioxide, nitrogen dioxide, and carbon dioxide" are all detected by these sensors. The data collected by sensors is sent to the data register from there it is sent to the Machine learning Training module (ML) and the comparison is done with real-time data and trained data. If the values increase beyond the tolerance level the system will give the alarm and release the oxygen.**

***Keywords*—Artificial Sensing Methodology; Machine Learning; Toxic gases; Tolerance Detections**

I. INTRODUCTION

TOXIC gas pollution is defined as any physical, chemical and biological component that affects the inherent properties of the atmosphere. Toxic gases are produced by a variety of sources, including automobiles, household combustion devices, forest fires, and industrial processes. Mainly industrial developments like Fertilizer Industry, Leather Industry, Alcohol Industry, Sugar Industry, Pharmaceutical Industry, Garbage Disposal, Power plants, oil refineries, etc, those are the main sources and areas of toxic gasses released. Pollutants of major public health concern include Methane, Chlorofluorocarbons, Particulate Matter-PM, Nitrogen Dioxide-NO2, Carbon Monoxide-CO, Lead-Pb, Ozone-O3, Carbon Dioxide-CO2, Sulfur Dioxide-SO2, Volatile Organic Compounds (VOCs) etc. Toxic gasses kill an estimated seven million people worldwide every year.

Accidents resulting from poisonous gas leaks can be severe. It has the capacity to have a major impact on people's health. Such as heart disease, lung cancer, skin problem, eye irritation, risk of respiratory infections, and also in all living things.

II. ABOUT THE IOT

The next step in the evolution of communication is the Internet of Things (IoT) technologies. In IoT, technologies physical items can be used to empower the environment by receiving, creating, and sharing the data in a seamless manner. This technology helps to automate procedures and allow inert physical objects to act without human intervention. Existing and new IoT applications have a lot of promise to improve user efficiency, comfort, and automation. privacy, authentication, high security, and attack recovery are all required when implementing such a rapidly evolving trend. In order to establish end-to-end secure IoT systems, it is vital to make the appropriate changes to IoT application architecture. IoT supports many applications in that one of the applications is detection of toxic gases using various sensors. From these sensors data collected and processed for further analytics. These sensors are well trained and arranged in an organized manner in the chamber, which is called a sensor chamber. This sensor chamber is connected to the device called the data register, this connection can be done through either wired or wireless mode, it is based on the requirement of the environment. The sensors used to detect the toxic gasses are MQ-7, MQ-135, MQ-136, SO2-D4, and NO2-D4

III. RELATED WORK

A difficult undertaking for the gas detecting devices used in several applications is the quick identification of flammable and toxic gas substances within an incredibly short reaction time [1]. A sophisticated hybrid method that combines recurrent and convolutional neural networks and relies on the long short-term memory module. This suggested approach The accuracy of this methodology, according to the 10-cross validation method, is 84.06 percent at 0.5 seconds and 98.28 percent at 4 seconds. With such a huge number of attributes, one can continuously calculate rapid gas acknowledgment with unparalleled accuracy and anti-float capacity for various IoT applications.

To create a portable electronic nose that can detect both volatile and non-volatile smells. The goal is to implant it on a humanoid robot by the halfway point [2]. The demonstrations for identifying pure organic juices (Pineapple, Orange, Apple, and Grenade), explosive scent, butane gas, and damaged eggs were shown. The focus of this research was to demonstrate characterization capabilities as the first step toward implanting the E-Nose in a humanoid robot in the future. In tightly constrained natural conditions, average precision of 98 percent with time handling ranging from 30 to 60 seconds was achieved.

Authors are with the Department of Networking and Communications College of Engineering and Technology SRM Institute of Science and Technology, Kattankulathur, India (e-mail: ds5929@srmist.edu.in, saravanm7@srmist.edu.in).

"Principal Component Analysis" (PCA) and the "k-Nearest Neighbors" (KNN) method were both used in the grouping system.

The typical identifier model system has been developed to the point where it can accurately control the safety of the air in any neighborhood under a variety of natural conditions [3]. In this study, very poisonous chemicals, electronic nose (e-nose) sensors, natural identifier neural learning (NINL), artificial neural network (ANN), and are all used. "Field Programmable Gate Arrays" (FPGA) exists to reduce the operating time of our identification model and support the equipment a piece of the e-nose for controlling, then, the gases distinguishing proof in any mind-boggling genuine working circumstances. This approach has helped to streamline the operating circumstances, from research lab conventional circumstances to genuine working conditions. To ensure ongoing good air quality monitoring, this is the justification.

Nitrogen oxides, CO2, carbon dioxide, and hydrocarbons are among the pollutants released by automobiles. [4] The ratio of fuel/vehicle, weather, and driving habits all influence how much each of these pollutants is produced. The model is trained using a technique called decision forest regression. The model is taught using a sizable amount of the acquired data on air pollution. Since this system simply keeps track of three variables, it can be expanded by taking into account additional variables that specifically affect how polluting cars are. The primary goal of the smart emission surveillance system is to make it superior to the existing system in terms of time savings, creative potential, operational effectiveness, and ease of use. When compared to traditional emission testing, using smart technologies not only improves environmental quality but also helps automobile owners save a lot of needless hassles.

In order to assess the adequacy of the system's separation effect, several VOCs (Volatile Organic Compounds) detections are carried out in this study using an "High Field Asymmetric Waveform Ion Mobility Spectrometry" (FAIMS) system that has been created [5]. The relationship between the waveform and the compensating voltage is then spoken about. The comparative trials serve as a helpful guide for later FAIMS optimization of the detection of harmful VOC contaminants.
The results of the experiments showed that this system performed well in terms of separation in the detection of harmful VOC contaminants. To offer useful reference data for the next optimization, a number of comparative experiments were conducted.

Toxic gases including carbon monoxide, carbon dioxide, nitrogen dioxide, etc. are primarily to blame for air pollution. The array of sensor consists of three MQ-3, MQ-6, and MQ-135 sensors. ANN, BP, PCA, SVM, LDA, and other sorts of algorithms can be utilised for classification. [6] Using Visual Basic 6.0, the backpropagation algorithm is produced. The outcomes are presented as percentages. 100 iterations are provided by the created algorithm. Increasing the amount of inputs will increase the system's accuracy. Additionally, the MQ-series sensors used here are affordable and take less time to heat up.

Many particle and hazardous gases are produced as a result of increased urbanisation and industrialisation, poor emission control, and sparse usage of catalytic converters[7]. This research suggests locating automobiles that generate smoke and cause air pollution in a certain area to be monitored using IoT. The intended approach makes use of both RFID (Radio Frequency Identification) and wireless sensor network (WSN) technology to achieve this. The sensor nodes have wireless communication capabilities and are outfitted with gas sensors.

Use a Bayesian inference approach to solve the gas identification problem. Data of eight gases, including C3H8, C6H6, CH2O, CL2, CO, CO2, NO2, and SO2, are collected in the lab to validate the efficacy of this approach[8]. 99.40% overall accuracy rating for the experimental data set. The primary benefit of this classification approach is that, unlike other cutting-edge pattern recognition algorithms utilised in the electronic nose applications, it offers a closed-form solution and does not necessitate manual parameter tuning.

This approach involves the intelligent collection and decomposition of garbage, maximizing the usefulness of the waste and effectively reducing the actual waste. Regarding the various permutations of the three sensor values. such as the level of biodegradable and non biodegradable garbage, and the concentration of toxic gas, a machine learning approach called KNN is utilised to generate an alarm message. [9] With an accuracy rate of 93.3%, this model employs the machine learning technology KNN to send alert messages to the relevant authorities in the society.

When subjected to UV light at room temperature, data on gas sensing was gathered for NO2, ethanol, SO2, and H2 alone and in mixtures with the gases H2O and O2. [10] For the classification of gas type, four supervised machine learning methods, including "Naive Bayes (NB) (kernel), Support Vector Machine (SVM), Decision Tree, and K-Nearest Neighbor (KNN)" were trained and optimised utilising their key parameters. The results show that the NB and SVM classifier models performed perfectly on our dataset. In addition, compared to readily accessible commercial metal-oxide sensors, the designed array device requires relatively less power.

IV. PROPOSED ARCHITECTURE

This proposed architecture figure 1 is divided in to four modules (A). Input module, (B). Sensor Chamber, (C). Data Register and Training Module, (D). Protection Module.

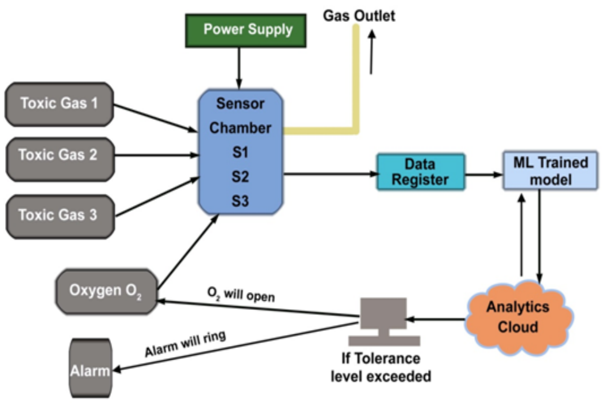

Fig. 1. Proposed system architecture

A. Input module

Input module designed for inlet the various types of gases such as "ammonia, nitrogen dioxide, carbon monoxide, carbon dioxide, & alcohol" etc. In this work three types of gases are used such as Carbon Dioxide, Sulfur dioxide and Nitrogen dioxide.

B. Sensor Chamber

The sensors are well designed and arranged in an organized manner in the chamber, which is called a sensor chamber. These toxic gases are sent to the sensor chamber figure 2 which contains sensors MQ2, MQ136 and MQ138. These sensors are used to identify the respective toxic gases, once the sensors identify the toxic gases they send readings to the data register.

Fig. 2. Sensor Chamber

B.1. About the sensors

1) Carbon Dioxide Gas Sensor

The MQ2 sensor figure:3 is a dual-channel pyroelectric detector. These CO2 sensors are intended for applications such as indoor air quality (IAQ), safety, combustion, and high CO2 process control. Simply apply the proper linearization constants in software for your needed range, and the MQ2 covers the whole concentration range of measurement.

TABLE I
USAGE OF SENSORS

Sl.No	Sensor Name	Applications
1	MQ2	Carbon dioxide
2	MQ136	Sulfur dioxide
3	MQ138	Nitrogen dioxide

Table I illustrates the sensors name and applications

Fig. 3. MQ2 Sensor – Used to detect Carbon Dioxide

2) Sulfur Dioxide Gas Sensor

The MQ136 in figure:4 features a high signal level paired with a low zero current, allowing for a resolution of less than 1ppm and a 200 ppm operating range for safety applications. The sensors can be used in both stationary and portable instrumentation. The MQ136 sensors provide long-term detection reliability.

Fig. 4. MQ136 sensor Used to detect Sulfur Dioxide

3) Nitrogen dioxide Gas Sensor

The MQ138 no2 sensors in figure:5 offer a high signal level and a low zero current, allowing for a resolution of 5-ppm and a 20-ppm operating range. Fixed sites, portable safety equipment, urban air monitoring, and stack gas analyzers can facilitate the sensors. The NO2 sensors offer reliable long-term detection performance.

Fig. 5. MQ138 sensor Used to detect Nitrogen Dioxide

TABLE II
SPECIFICATION SUMMARY OF GAS SENSORS

Specification Summary	CO2	NO2	SO2
Range of operation - ppm	0 to 5000	0 to 20	0 to 20
Resolution -ppm	< 1.5	0.1	< 0.2
Time of Response (t90) (s)	< 25	< 35	< 15
Sensitivity (nA/ppm)	30 to 50	-200 to -450	180 to 360
Overgas Limit (ppm)	8000	60	50
Range of Temperature - (oC)	-20 to 50	-20 to 50	-20 to 50
Range of Pressure-(kPa)	80 to 120	80 to 120	80 to 120
Range of Humidity - (%rh)	15 to 90	15 to 90	15 to 90
Operating life (months)	>24	> 24	>24
Range of operation - ppm	0 to 5000	0 to 20	0 to 20
Resolution - ppm	< 1.5	0.1	< 0.2

Table II Illustrates the Specification Summary of gas sensors

C. Data Register and Training Module

1) Data Register

The data register is a system that records data over time and stores the data in the register containing the date, time, gas name, and reading of the gas.

2) Training module - Machine Learning (ML)

The data register collects the information from the sensor's chamber and transfers it to the ML module. An ML module is a system that contains trained algorithms to perform the resulting analytics and things connected to wired or wireless networks and send and receive data. From the ML module, the data is sent to the analytics cloud where the data are stored for the feature process.

D. Protection Module.

The ML module compares with the trained data set, and if the tolerance level of gases is exceeded it automatically opens the oxygen cylinder valve to dilute the concentration of the gases so that the effect of the gas will reduce and the tolerance level will be maintained in control.

It uses sensors like MQ-7, MQ-135, MQ-136, SO2-D4, and NO2-D4. The flow diagram Figure 3 of the system uses a gas inlet, inlet chamber, sensor chamber, data register, an ML Training module, tolerance checking system, alarm, and oxygen outlet. The inlet chamber consists of samples of gasses like "carbon monoxide, sulfur dioxide, carbon dioxide and nitrogen dioxide". The sensor chamber contains sensors like MQ-7, MQ-135, MQ-136, SO2-D4, and NO2-D4. The sensor chamber is used to identify the gasses present in the inlet chamber. The information is sent to the Data register from there it moves to the ML Training module and the comparison is done with real-time data and trained data. If the values increase beyond the tolerance level the system will give the alarm and release the oxygen.

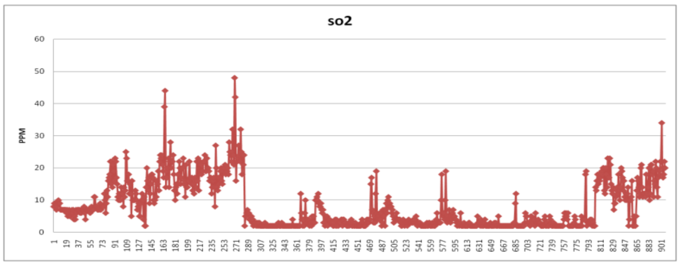

Fig. 6. Sensor reading for so2

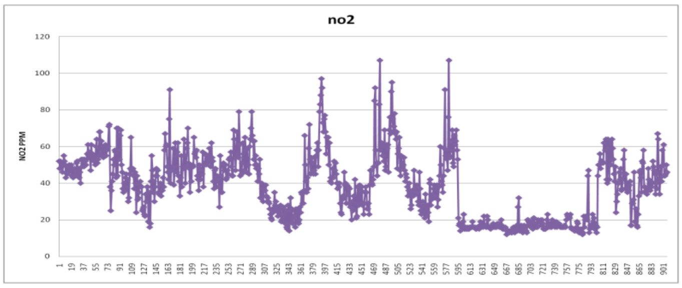

Fig. 7. Sensor reading for no2

TABLE III
DATA REGISTER READINGS

SI.No	so2	no2	co2
1	4.8	0.1	9519.37
2	0.3	2.3	10025.13
3	0.6	0.7	3286.77
4	2.6	4.2	5514.90
5	4.7	1.2	12817.42
6	6.4	1.1	3468.93
7	5.4	7.1	3997.21
8	1.6	0.7	15262.05
9	3.5	0.9	12685.36
10	1.2	1.2	4235.12

Table III Illustrates the Sensors dataset

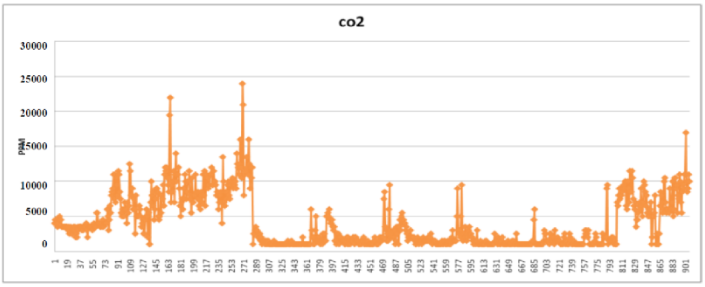

Fig. 8. Sensor reading for co2

Figure 6,7, and 8 Illustrates the Sensor reading of toxic gases, That is SO2, NO2, and CO2

V. CONSTRUCTION OF DATASET

Table III shows the sensor readings, in every certain time interval inlet opened and recorded sensor readings taken from the data register to construct the dataset based on the air quality index (AQI). AQI is calculated based on the tolerance level of gases. The tolerance levels of gases are divided into six categories shown in the table IV tolerance level of gases. The values in table IV are in ppm.

TABLE IV
TOLERANCE LEVEL OF GASES

Gases	Good	Moderate	Unhealthy for Sensitive Groups	Unhealthy	Very Unhealthy	Hazardous
SO2	0 to 0.1	0.1 to 0.2	0.2 to 1.0	1.0 to 3.0	3.0 to 5.0	> 5.0
NO2	0 to 0.2	0.2 to 0.4	0.4 to 0.6	0.6 to 0.9	0.9 to 1.2	> 1.5
CO2	0 to 5,000	5,000 to 10,000	10,000 to 15,000	15,000 to 30,000	30,000 to 40,000	40,000 to 50,000

Table IV Illustrates the tolerance level of gases.
Note: The values in table IV are in ppm

Based on the tolerance levels the target value is fixed for the dataset. That is S_t, N_t and C_t each target value is divided into six categories that is from 1 to 6.
For example:
G1[i] = so2 gas; for i = s1 to s6
G2[i] = no2 gas; for i = n1 to n6
G3[i] = co2 gas; for i = c1 to c6
Therefore G[i] = {g1,g2,g3,…gn}

S_t = is target value of So2
N_t = is target value of No2
C_t = is target value of Co2
t = target value.

Where as
S_t = {s1, s2, s3, s4, s5, s6}
N_t = {n1, n2, n3, n4, n5, n6}
C_t = {c1, c2, c3, c4, c5, c6}

Whereas S_t, N_t, and C_t are the target value of so2, no2 and co2 respectively.

TABLE V
TARGET RANGE OF GASES

Gases	Target Range					
St	s1	s2	s3	s4	s5	s6
So2	0 to 0.1	0.1 to 0.2	0.2 to 1.0	1.0 to 3.0	3.0 to 5.0	> 5.0
Nt	n1	n2	n3	n4	n5	n6
No2	0 to 0.2	0.2 to 0.4	0.4 to 0.6	0.6 to 0.9	0.9 to 1.2	>1.5
Ct	c1	c2	c3	c4	c5	c6
Co2	0 to 5,000	5,000 to 10,000	10,000 to 15,000	15,000 to 30,000	30,000 to 40,000	40,000 to 50,000

Table V Illustrate the Target range of gases

TABLE VI
DATASET WITH TARGET VALUES

SI.NO	SO2	NO2	CO2	ST	NT	CT
1	4.8	0.1	9519.37	S6	N1	C2
2	0.3	2.3	10025.13	S3	N6	C3
3	0.6	0.7	3286.77	S3	N4	C1
4	2.6	4.2	5514.90	S4	N6	C2
5	4.7	1.2	12817.42	S5	N5	C3
6	6.4	1.1	3468.93	S6	N5	C1
7	5.4	7.1	3997.21	S6	N6	C1
8	1.6	0.7	15262.05	S4	N4	C4
9	3.5	0.9	12685.36	S5	N4	C3
10	1.2	1.2	4235.12	S4	N5	C1

Table VI Illustrate the Dataset with target values

VI. ALGORITHM

The following algorithm is used to set the target values and calculate the AQI

Initialize Gases to G1,G2,G3 (G1=so2,G2=no2,G3=co2)
Initialize target value of gases to St,Nt,Ct
Initialize target value to t
Input the Data register reading

Calculate the target value for G1 (St)
G1 = St(so2)

Initialize St to zero
if the so2 is less than or equal to 0.1
set St equal to s1
if the so2 is greater than 0.1 and less than or equal to 0.2
set St equal to s2
if the so2 is greater than 0.2 and less than or equal to 1.0
set St equal to s3
if the so2 is greater than 1.0 and less than or equal to 3.0
set St equal to s4
if the so2 is greater than 3.0 and less than or equal to 5.0
set St equal to s5
if the so2 is greater than 5.0
set St equal to s6
return St

Calculate the target value for G2 (Nt)
G2 = Nt(no2)

Initialize Nt to zero
if the no2 is less than or equal to 0.2
set Nt equal to n1
if the no2 is greater than 0.2 and less than or equal to 0.4
set Nt equal to n2
if the no2 is greater than 0.4 and less than or equal to 0.6
set Nt equal to n3
if the no2 is greater than 0.6 and less than or equal to 0.9
set Nt equal to n4
if the no2 is greater than 0.9 and less than or equal to 1.2
set Nt equal to n5
if the no2 is greater than 1.5
set Nt equal to n6
return Nt

Calculate the target value for G3 (Ct)
G3 = Ct(co2)

Initialize Ct to zero
if the co2 is less than or equal to 5000
set Ct equal to c1
if the co2 is greater than 5000 and less than or equal to 10000
set Ct equal to c2
if the co2 is greater than 10000 and less than or equal to 15000
set Ct equal to c3
if the co2 is greater than 15000 and less than or equal to 30000

```
  set Ct equal to c4
 if the co2 is greater than 30000 and less than or equal to 40000
  set Ct equal to c5
 if the co2 is greater than 50000
  set Ct equal to c6
 return Ct

Calculate the AQI value for St, Nt, Ct
 Initialize AQI to zero
  if the St is greater than Nt and greater than Ct
   set AQI equal to St
  if the Nt is greater than St and greater than Ct
   set AQI equal to Nt
  if the Ct is greater than Nt and greater than St
   set AQI equal to Ct
  return AQI
```

TABLE VII
DATASET WITH AQI VALUES

SI.No	so2	no2	co2	St	Nt	Ct	AQI
1	4.8	0.1	9519.37	S6	N1	C2	9519.37
2	0.3	2.3	10025.13	S3	N6	C3	10025.13
3	0.6	0.7	3286.77	S3	N4	C1	3286.77
4	2.6	4.2	5514.90	S4	N6	C2	5514.90
5	4.7	1.2	12817.42	S5	N5	C3	12817.42
6	6.4	1.1	3468.93	S6	N5	C1	3468.93
7	5.4	7.1	3997.21	S6	N6	C1	3997.21
8	1.6	0.7	15262.05	S4	N4	C4	15262.05
9	3.5	0.9	12685.36	S5	N4	C3	12685.36
10	1.2	1.2	4235.12	S4	N5	C1	4235.12

Table VII Illustrate the Dataset with AQIvalues

After the target value classification is finished, the dataset is then split into two parts: one portion is reserved for the dataset that will be used for training, and the other half is reserved for the dataset that will be used for testing, with the ratio being 70:30 accordingly. Now the dataset is prepared to be fitted with a model.

VII. AIR QUALITY INDEX LEVEL OF HEALTH CONCERN

The following information is given by the central pollution board (CPCB) and ministry of environment, forest and climate change.

0-50 is considered Good. The colour code of good is dark green, it causes minimal impact for health.

51-100 considered as satisfactory the colour code of satisfactory is light green. People who are sensitive to it may have some moderate breathing difficulty.

101-200 considered as moderate the colour code of moderate is yellow. Those who suffer from lung illness, asthma, or heart disease may experience difficulty breathing as a result of this.

201–300 - considered as Poor the colour code of poor is orange. Most people, with continuous contact, may experience breathing difficulties, and persons who already have heart disease may also experience pain.

301–400 considered as Very Poor the colour code of very poor is red. Long exposure to this substance may induce respiratory sickness. Those who already have respiratory or cardiovascular problems may feel its effects more strongly.

401-500 - considered as Severe the colour code of severe is dark red. Even in healthy people, it can create breathing problems, and in persons who already have lung or heart disease, it can cause major health problems.

The following table illustrates the air quality standards of central pollution control boards

TABLE VIII
STANDARDS FOR AIR QUALITY ESTABLISHED BY CENTRAL POLLUTION CONTROL BOARDS

AIR QUALITY INDEX (AQI)	CATEGORY
0-50	Good
51-100	Satisfactory
101-200	Moderate
201-300	Poor
301-400	Very Poor
401-500	Severe

VIII. MACHINE LEARNING ALGORITHMS

In this work three machine learning techniques are used to train the dataset such as Decision Tree, Random Forest, and KNN techniques.

A. Decision Tree Algorithm

The algorithm known as the Decision Tree is classified as a supervised learning method. Regression and classification issues can be resolved using the decision tree technique. A Decision Tree can be used to construct a training model to predict a target variable's class or value. This model is built by learning streamlined decision rules that are obtained from previous data (training data). When using a decision tree to forecast a record's class label, we begin at the root of the tree. Here root nodes are considered as types of gases. We compare the root and record attributes. Following the comparison, the corresponding branch is followed.

B. *Random Forest Algorithm*

Instead of using the forecast from just one decision tree, the random forest method averages them all and determines the final output based on which tree's prediction received the most votes overall. A classifier known as Random Forest takes the average of its many decision trees applied to various subsets of a given dataset in order to increase the accuracy of predictions made using that dataset. The dataset used for the decision tree algorithm, the same dataset is used for the random forest algorithm. The greater number of trees in the forest prevents higher accuracy and overfitting.

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

The K-Nearest Neighbor algorithm belongs to supervised learning algorithms. Even though the K-NN method can be used for both regression and classification problems, classification issues are where it is most frequently applied. K-NN is a non-parametric approach, hence it does not assume anything about the data being analysed. Rather than immediately learning from it, it keeps the training dataset in storage. Instead, it performs an action while classifying data by using the dataset. The KNN approach simply preserves the data during the training phase, that is, it saves the sensor data and its classification during the training phase and, the system automatically assigns newly received information to a grouping that best fits it.

IX. Algorithm Explanation

Algorithm:- Reading and processing sensor data.

```
Input: Sensor value
Output: Ring Alarm and open O2 value
 Function Threshold Control()
{
Sulfur dioxide (SO2) = values_read_by_MQ136
Carbon dioxide (CO2) = values_by_MQ2
Nitrogen dioxide (NO2) = values_by_MQ138
Threshold_of_MQ136 = 20 (in ppm);
Threshold_of_MQ2  = 5000 (in ppm);
Threshold_of_MQ138 = 20 (in ppm);
Print values_by_MQ136,
Print values_by_MQ2
Print values_by_MQ138,
counter=0;
If (SO2 > Threshold_for_MQ136)
{
Ring Alarm_MQ136 set High;
No Alarm _MQ136 set Low;
counter=counter+1;
}
If (CO2 > Threshold_for_MQ2)
{
Ring Alarm_MQ2 set High;
No Alarm _MQ2 set Low;
counter=counter+1;
}
If (NO2 > Threshold_for_MQ138)
{
Ring Alarm_MQ138 set High;
No Alarm _MQ138 set Low;
counter=counter+1;
}
else {
Ring Alarm_for_MQ136 set High;
No Alarm _for_MQ136 set Low;
Ring Alarm_for_MQ2 set High;
No Alarm _for_MQ2 set Low;
Ring Alarm_for_MQ138 set High;
No Alarm _for_MQ138 set Low;
}
If(counter>=3)
{
wait(3 minutes);
Set open O2 value
}
```

X. Results and Discussion

In This work following algorithms Decision Tree, Random Forest, and KNN are implemented in python using the data set size is 20110 rows. The data is preprocessed and trained using the above stated algorithms by splitting the dataset into 70:30 ratio, training (70 percent) and testing (30 percent). The performance of Decision Tree, Random Forest, and KNN is compared. The performance was evaluated using three performance metrics: sensitivity, specificity, and accuracy.

A. *Sensitivity*

Sensitivity is to measure that evaluates models
Ability to identify the true positive rate.

$$\textbf{Sensitivity} = \frac{\textbf{True Positives}}{\textbf{True Positives} + \textbf{False Negatives}}$$

B. *Specificity*

Specificity is to measure that determines the
proportion of the actual negative rate.

$$\textbf{Specificity} = \frac{\textbf{True Negatives}}{\textbf{True Negatives} + \textbf{False Positives}}$$

C. *Accuracy*

Accuracy is used to predict the exactness of the machine learning model.

$$\text{Accuracy} = \frac{\text{True Negatives} + \text{True Positives}}{\text{True Positives} + \text{False Positives} + \text{True Negatives} + \text{False Negatives}}$$

D. *Therefore*

True Positive (TP): The total amount of potentially hazardous situations that were found.

True Negative (TN): The total amount of different typical circumstances.

False Positive (FP): As expected, the total amount of contamination conditions is recognized.
False Negative (FN): The total amount of non-toxic situations that have been discovered.

TABLE IX
PERFORMANCE EVALUATION

ALGORITHM	SENSITIVITY	SPECIFICITY	ACCURACY
DECISION TREE	84.46	88.65	85.56
RANDOM FOREST	78.76	84.35	83.78
KNN	76.46	87.78	81.24

Table IX Illustrates the Performance evaluation

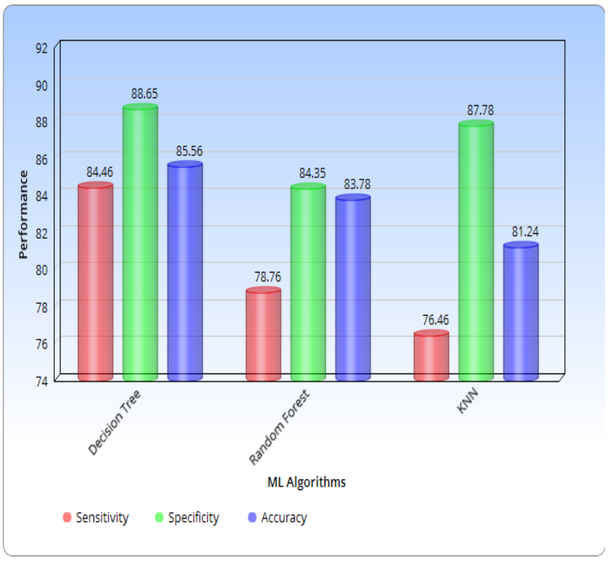

Fig. 9. Illustrates the Performance evaluation of algorithms

XI. CONCLUSION

E-nose devices serve a significant and vital part in human safety when it comes to many sorts of dangerous and toxic gases. The sensors collect data on a regular basis in both normal and high-pollution parts of the city, and the data is then analysed using machine learning methods to identify harmful substances. In the first section of this work, two independent real-time research datasets are used to demonstrate the machine learning-based E-nose system. This paper examines the many components of machine learning in depth, as well as the outcomes of experiments on two datasets. In future this toxic tolerance level will be analyzed with human respiratory system.

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