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Harmful gases detection using artificial neural networks of the environment

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ABSTRACT

This work describes a small, low-cost electronic nose device which can detect harmful substances that can harm human health, such as flammable gas like acetone, ethanol, butane as well as methane, among others. An artificial olfactory instrument consists of a set of metal oxide semiconductor sensors as well as a computer-based communications channel for signal gathering, proceeding, and presentation. We used three sensors instead of six, and the results were plotted as a variance, score as well as loading plot with cross-validation. For gas identification, we use artificial neural network (ANN) and compare them to parallel factor analysis. Electronic nose (e-nose) has provided numerous benefits in a variety of logical study disciplines. Our goal is to create a sensor exhibit framework that can discriminate the most exceedingly contaminated gases while also being extremely responsive, precise, and less power consuming. Thus, for gas detection, we employ an ANN as well as make a comparison of results with parallel factor analysis (PARAFAC).

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1. INTRODUCTION

An electronic nose is a sensing device that consists of a collection of gas sensing material that reacts to a variety of chemical particles. Many conclusions concerning quality of the air and toxin can be drawn based on the outputs from the sensors. In three areas, they have demonstrated tremendous promise and utility: food safety, diagnosis of diseases, and environmental monitoring. In the food industry, electronic noses (e-noses) have been used to ensure consumer quality and safety. Food quality, ageing, and infiltration during manufacturing, shelf life, and authenticity validation are some of the features that have already been addressed in this sector. The goal of e-nose implementation is to evaluate olfactory profiles [1] in beer and automating the quality inspection process in the industry [2]. Created an e-nose to classify scents from synthetic flavors including grapes, strawberry, mango, as well as orange. To warn of rancidity [3], developed an e-nose that tracks pecan changes during storage [4]. Investigated utilization of an electronic nose to detect scents associated with formalin contamination in seafood [5]. Suggested electronic nose to aid with authenticity testing of items like as honey, meat, plant oils as well as milk to prevent product adulteration [6]. Introduced e-nose differentiating pork from beef to deter meat merchants from committing food fraud. Wang *et al.* [7] used an e-nose to analyze the freshness of fruits, vegetables, and meat within a residential refrigerator. People's capability to identify diseases through their sense of smell has been crucial in clinical diagnosis. E-nose have ability to be quite useful significant diagnostic technique for diseases for people, plants, as well as animals by making it easier to identify volatile organic compounds containing bacterial pathogens [8]. An air toxin is a material that is widely recognized and that has the potential to have a negative influence on humans and natural structures all over the world. As a result of the rise in contaminated gases, there is a growing demand for territory and the tracking of ozone damaging compounds [9]. In any event, we would almost likely manage trademark gases that are passed on by solid waste approaches in this paper, and we can give consideration to indoor air damages in light of actuality of scenario [10]. The best lessons learned regarding zone programmes were that the most often sensors in utilization are sensitive to changes in barometric circumstances [11], [12]. E (electronic) nasal reason is to keep track of the area flood and document the association between moving nose actions and notice drive [13]. In light of the fact that thing consistency is vital for maintaining client seal reputation and fulfillment, quality control (QC) of aroma qualities of supplied stock is of paramount importance [14]. Figure 1 is the basic diagram of electronic nose, which is used to sense the gases. It has five blocks: 1st include odor (to sense), 2nd include gas sensor array (MOS sensors), 3rd block is signal transducer (that converts non-electrical energy to electrical voltage signal), 4th block is pattern recognition that recognize the voltage signal and 5th block is discrimination and classification that classify these voltage signal for output.

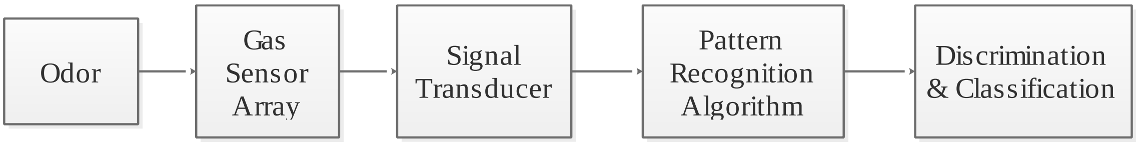


Figure 1. Block diagram of electronic nose

Volatile organic compound outpourings are strongly linked to the treating the soil methodology phases [15]-[17], which include disclosure of hazardous or perilous substance leaks from pipelines or modern-day facilities, as well as early forewarning of a swarm of dangerous smells. The signals from the sensors were spectrally evaluated in this paper using an artificial neural network (ANN), and parallel factor analysis (PARAFAC) methods. The organization of the paper is that section defines the introduction which includes the description of MOS sensor and e-nose. Section 2 defines the proposed method, section 3 defines the methods and section 4 defines the results and discussion.

Many writers spoke about the ANN methods, pattern recognition approaches, and other works during this conference. Xibilia *et al.* [18] suggested a gas monitoring device for industrial applications that used a gas sensor module whose results are further analyzed by a neural network, according to some of the authors. Mishra and Rajput [19] proposed two independent ANN blocks to categories and quantify the gas, allowing for real-time gas monitoring. Soomro and Jilani [20] developed a gas safe registered monitoring system for coal mining that uses sensors to detect gas concentrations (CO, methane temperature, as well as humidity), a ZigBee wireless network to communicate, as well as an artificial neural network to estimate gas concentration levels and alarm hazards. Natural gas fields are extensively scattered around the world, and organic gas monitoring application circumstances vary greatly, ranging from frigid and dry inland regions to warm and humid offshore gas fields [21].

The reactions of the sensors for every gas, as well as a mixing of two or maybe all of them, were examined and assessed by Lin *et al.* [22]. Every sensor replied to these 4 (Four) gases and the value of each sensor to mixture gases was less than the sum of the individual gas responses. Noorsal *et al.* [23] define the use of ANNs in the signal processing of quartz crystal microbalance detectors for volatile organic compound (VOC). The optimal topology of the neural network was discovered with a trial-and-error process in which various numbers of hidden nodes were employed in the hidden layer to acquire the optimal layer size as well as weight values. Jasinski *et al.* [24] defines the electronics nose is made up of an arrays of partial specification of electrochemical gas sensors and pattern recognition methods. For the goal of determining the concentration of target gases, three multivariate regression methods were used: partial least squares (PLS), least-squares support vector regression (LS-SVM), plus ANN. Shahid *et al.* [25] said that the creation of the electronic nose (E-nose), which uses an array of SnO2 gas sensors that detect and quantify hazardous and odorless gases including carbon mono-oxide and methane has gotten a lot of attention. This research uses an ANN plus least squares regression (LSR) to construct a classifiers and estimations for sensor cross reactivity. Zhao *et al.* [26] proposed a one-dimensional deep convolution neural network (1D-DCNN) with a multi-label-way-based approach for widely and reliably extracting and categorizing mixed gases.

2. PROPOSED METHOD
2.1. Parallel factor analysis

PARAFAC is used to extract the sample component of scent. PARAFAC is supposition of principle component analysis to all extra probable demand clusters, but some of characteristics of strategic approach are really quite different in comparison to normal including there may be no modernization issue in parallel factor analysis. In PARAFAC unvarnished spectra can be recovered from multi-way unearthly records. In this investigation, PARAFAC was connected to a few dimensional clusters.

The error minimization is done using the exchanging minimum squares (ALS) method. It uses the calculation below to repeatedly generate the stacking patterns A, B, and C.

a) Pick quantity of parts, F (on the decision of F see next section).
b) Introduce B along with C.
c) To reduce square of error, gauge A from X, B, as well as C by slightest square relapse.
d) Gauge B as well as C in like manner.
e) Continue from (3) until you reach a point where, lines intersect (indicated by just little changes in fit or loadings)

2.2. Artificial neural network

ANNs are computational models that are designed just after biological neural networks seen in animal brains. Artificial neurons are collection of linked components or nodes in an ANN that mimic biological neural networks in a vague sense. Similar synapses in human brain, every connection may transmit a signal toward adjacent neurons. The signals are received by the neuron, which then evaluates them before sending them towards neurons with which it is associated.

The Figure 2 shows the pre-processing steps for ANN model. From input to output ANN works in three layers of pre- processing steps. This model is neural network training kit type that's performance is very good. All the steps are performing in well manner like gradient squared pattern and validation checks.

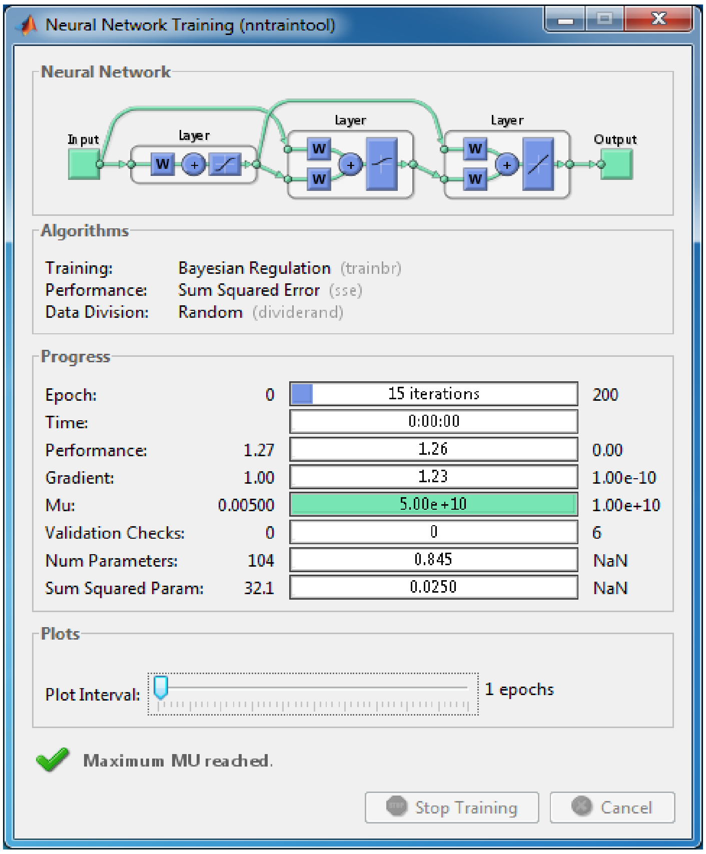


Figure 2. ANN model for pre-processing

3. METHOD

3.1. Cross-validation algorithm of ANN

As the training phase advances, an ANN's training error might be decrease. Moreover, ANN may start to takes benefit of quirks in the training data for some time, generally in the later phases of training. As a result, even while the prediction error continues to reduce, its generalization ability may begin to suffer. To eliminate over-fitting, one typical strategy is to terminate cross validation early. The training data is separated both training and testing sets in this procedure. The training process cannot end when the training error is minimized; rather, it will come to a halt when the validation error begins to rise. Since the validation data may contain many local minima, such termination condition is misleading. A simple requirement that terminates the ANN's training process is employed in the presented technique to reduce the negative influence of multimodal validation area on model generalization capability. Validation error is calculated at the ending of each 'L' training iteration. The training procedure is halted if validation error has improved for T consecutive times in contrast with the first 'L' training iterations (regardless of how great the increases are). The termination criterion's goal is to end ANN's training process whenever its validation error climbs T times in a row. Of that kind increases, not merely the periodic overfitting, are thought to signal the start of the final over-fitting. The suggested cross validation method's pseudo code is given:

Step 1. Initial: choose L, T, i value;
Step 2. Initial validation: if (iter=i) then compute E_{val} (gbest (iter)), otherwise continue training;
Step 3. Overfitting counter: set j=1;
Step 4. Validation: if (iter=i+Lxj) then compute E_{val} (gbest (iter)), otherwise continue training;
Step 5. Check error if (E_{val} (gbest (iter-i-Lxj))>E_{val} (gbest (iter)))i=i+Lxj go to step 2, otherwise j=j+1;
Step 6. Check stopping criteria: if (j < T) go to step 4 or else go to step 7;
Step 7. End: terminating the training algorithm do to over fitting with training set.

4. RESULT AND DISCUSSION

At testing repetition, each sensor reaction is saved as a content document: Time is the first segment, temperature is second. MICS 5521 is third, MICS 5135 is fourth, TGS2602 is fifth, TGS2600 is sixth, TGS2611 is seventh, and TGS 2620 is eighth. A MATLAB programmes that requests a dataset documents and imports it in accordance with length requirement. This site http://mrpt.org/robotics shows datasets [27].

4.1. Data information

The information assessment of data [27] for Acetone gas=(9*4230*6), in which the quantity of column=9, information sample=4230, and used sensors=6. The Propane gas information assessment [27] is (9*6191*6), in which the amount of column=9, information sample=6191, and used sensors=6. The information measurement for ethanol [27] gas is (9*6807*6), at which quantity of column=9, information sample=6807, and used sensors=6. TGS 2602=T1, TGS 2600=T2, TGS 2611=T3, TGS 2620=T4 sensors: MICS 5521=M1, MICS 5135= M2. To classify the gases, we use a combination of three sensors from each of the six sensors. Acetone is A, ethanol is E, and propane is P. Good: - when the distance between two gas clusters is large, detection is easy. Average: - although the distance between two gas clusters is small, they may be differentiated. Poor: - distance between two gases bunches is close/cover.

The outcome analysis is used to determine how well the parallel factor analysis examination was carried out on different sensors clusters. This process entails correlating sensor set reactions for three gases saved in the database. Diagram depicts all of the methods that have been needed in this investigation work at burns. Data can be recorded as well as taken from instrument using parallel factor analysis for only primary sensors, after which it computes change using score as well as loading plot, and then consider the outcome in terms of bunch wrapping as good, average, and poor. Here Figure 3 shows the entire identification procedure for electronic nose. In this there are six block. First block contains raw data; second block shows the higher dimension of raw data, third block shows the techniques which takes this higher dimension data to convert it into lower dimension data. The fourth block contains these lower dimension data. Fifth block shows the cluster of the gases which we used to detect and the six blocks shows the output of the cluster analysis.

The mentioned smelling system steps were used to collect scent information for each of the illustrations and trials; [0-20] sec: for first 20 seconds, the smell container was kept closed and separated from longing (pattern esteem); [20-30] sec: Jug was open for such 10 seconds (stabilization); [30-90] sec: electronics nose goal was placed closer to container after 30 seconds, at a distance of 10 cm, as well as recorded for 60 seconds. [90-X] sec: lastly, the source was removed, as well as the electronic nose was left to return to layout state for 10 minutes before the next chronicle. Table 1 shows the description of each sensor. First column include type of sensors, second detection materials, third contain voltage/resistance for sensor and fourth contains power.

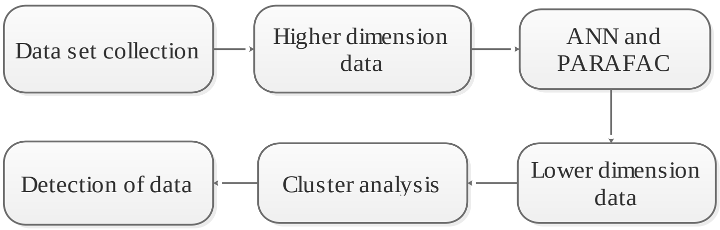


Figure 3. The suggested e-nose system's entire identification procedure

Table 1. Description of each sensor

Sensor	Detection materials	Voltage/R_{Base}	Power
MICS 5521	CO, hydrocarbons (HC), and VOC.	5 V DC, 74 Ω	76 mW
MICS 5135	CO, HC, ethanol, and VOC.	3.2 V, 97 Ω	102 mW
TGS 2602	Ethanol, Ammonia, Hydrogen, Toluene	5 V DC, 59 Ω	15 mW
TGS 2600	Methane, Ethanol, Iso-butane, CO, Hydrogen	5 V DC, 83 Ω	15 mW
TGS 2611	Methane, Ethanol, Iso-butane, Hydrogen	5 DC, 59 Ω	15 mW
TGS 2620	Methane, Ethanol, Iso-butane, CO, Hydrogen	5 DC/AC, 83 Ω	15 mW

Here Figure 4 shows the plot of raw data for sensor. The plot for score, loading and explained variance with cross-validation for ANN in Figures 5-8 and for PARAFAC in Figure 9. Score plot is used for the classification of cluster of gases. Loading plot discriminate the sensor performance as well as explained variance plot with cross- validation gives the cluster's variance from one to another parameter.

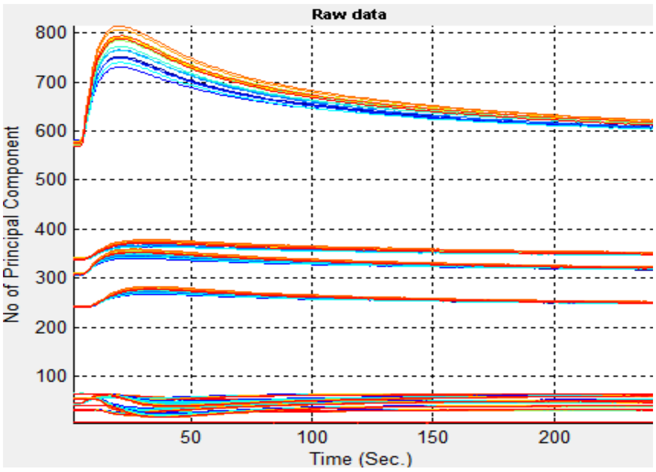
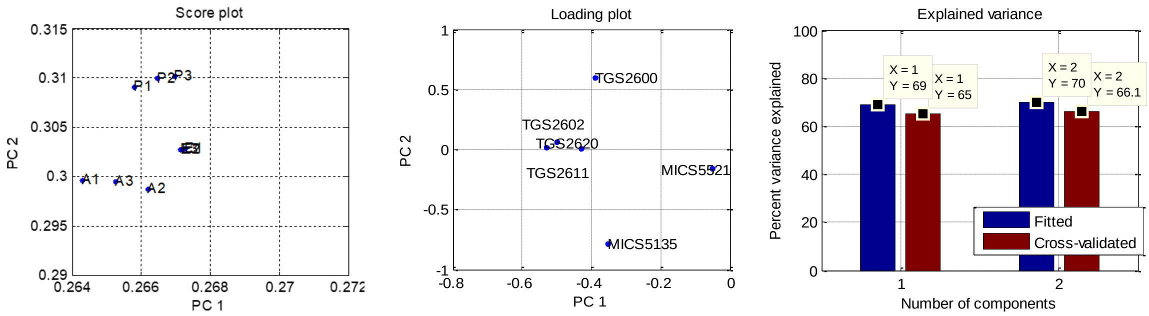


Figure 4. Plot of raw data for sensors [27]

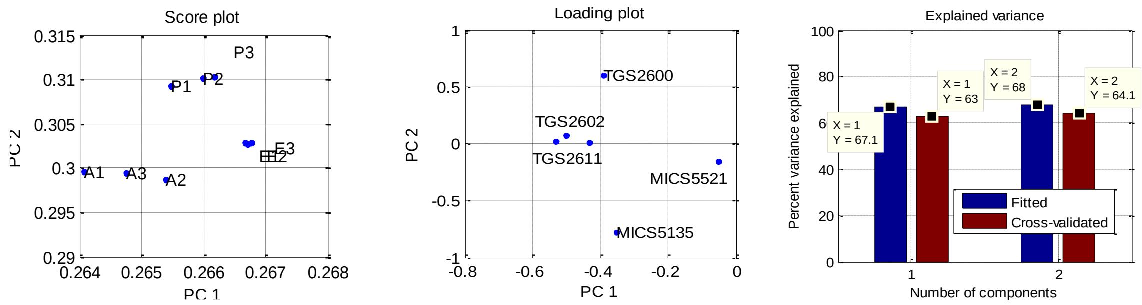
Figure 5 includes score, loading as well as explained variance plot for ANN technique. Figure 5(a) defines for the six sensors MICS 5521, MICS 5135, TGS 2602, TGS 2600, TGS 2611and TGS 2620 (M1M2T1T2T3T4). In Figure 5(a), acetone gas lies in the second block of PC1 as well as first as well as second block of PC2. The cluster of ethanol gas (E1, E2, E3) lies in third block of PC1 as well as second block of PC2. And we can see that third gas i.e. propane covering in fourth and fifth block of PC1 as well as first as well as second block of PC2. So that according to the score plot (Figure 5(a)), the detection of acetone and propane is good from each other and detection of propane and ethanol is average and acetone and ethanol is poor. In loading plot Figure 5(b) TGS2600, MICS 5521 and MICS 5135 are performing well and TGS 2602, TGS 2620 and TGS 2611are close with each-other so cannot differentiate the gases in well manner. Figure 5(c) show the explained variance plot with cross- validation on the basis of score and loading plot which gives the value for PC1 is 69 and for PC2 is 70 and for cross validation PC1 is 65 and PC2 are 66.1.



(a) (b) (c)

Figure 5. The score, loading and explained variance plot (a) score plot for ANN (M1M2T1T2T3T4), (b) loading plot for ANN (M1M2T1T2T3T4), and (c) explained variance plot for ANN (M1M2T1T2T3T4) with cross-validation

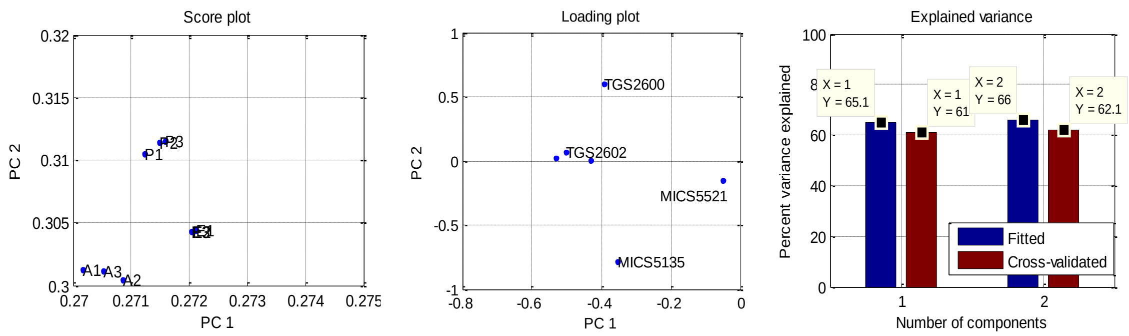
Figure 6 includes the score, loading as well as explained variance plot for ANN technique. Figure 6(a) defines for the five sensors MICS 5521, MICS 5135, TGS 2602, TGS 2600 as well as TGS 2611 (M1M2T1T2T3). In Figure 6(a) Acetone gas lies in the second block of PC1 as well as first as well as second block of PC2. The cluster of ethanol gas (E1, E2, E3) lies in third block of PC1 and third and fourth block of PC2. And we can see that third gas i.e. propane covering in fourth and fifth block of PC1 and second and third block of PC2. So that according to the score plot (Figure 6(a)) the detection of acetone and propane is good from each other and detection of propane and ethanol is average and acetone and ethanol is average. In loading plot i.e. Figure 6(b) TGS2600, MICS 5521 and MICS 5135 are performing well and TGS 2602 and TGS 2611 are close with each-other so cannot differentiate the gases in well manner. Figure 6(c) show the explained variance plot on the basis of score and loading plot which gives the value for PC1 is 67.1 and for PC2 is 68 and for cross validation PC1 is 63 and PC2 are 64.1.



(a) (b) (c)

Figure 6. The score, loading and explained variance plot (a) score plot for ANN (M1M2T1T2T3), (b) loading plot for ANN (M1M2T1T2T3), and (c) explained variance plot for ANN (M1M2T1T2T3) with cross-validation

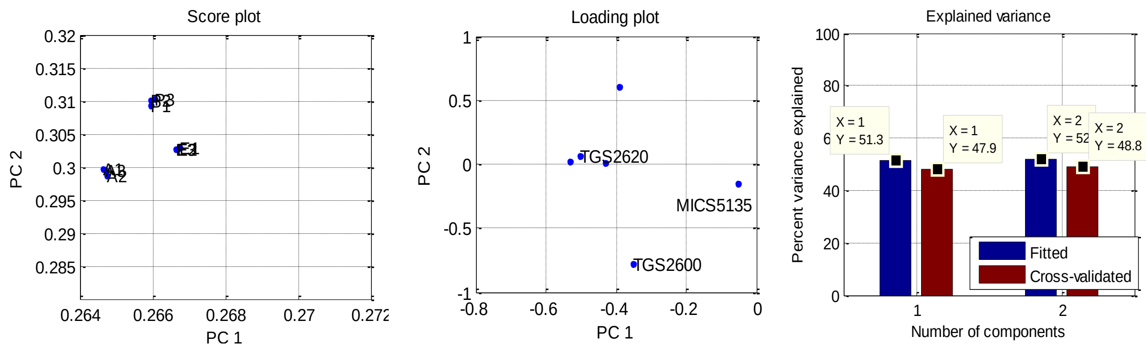
Figure 7 includes the score, loading as well as explained variance plot for ANN technique. Figure 7(a) defines for the four sensors MICS 5521, MICS 5135, TGS 2602 as well as TGS 2600 (M1M2T1T2). In Figure 7(a) acetone gas lies in the first block of PC1 as well as first as well as second block of PC2. The cluster of ethanol gas (E1, E2, E3) lies in first block of PC1 and third block of PC2. And we can see that third gas i.e. propane covering in third block of PC1 and second block of PC2. So that according to the score plot (Figure 7(a)), the detection of acetone and propane is good from each other and detection of propane and ethanol is good and acetone and ethanol is average. In loading plot Figure 7(b) all four sensors are distinct from each other so they can detect all gases in well manner. Figure 7(c) show the explained variance plot on the basis of score and loading plot which gives the value for PC1 is 65.1 and for PC2 is 66 and for cross validation PC1 is 61 and PC2 are 62.1.



(a) (b) (c)

Figure 7. The score, loading and explained variance plot: (a) score plot for ANN (M1M2T1T2), (b) loading plot for ANN (M1M2T1T2), and (c) explained variance plot for ANN (M1M2T1T2) with cross-validation

Figure 8 concludes score, loading and explained variance plot for ANN technique. Figure 8(a) defines for three sensors MICS 5135, TGS 2600 as well as TGS 2620 (M2T2T4). In Figure 8(a) the cluster of acetone gas lies in the first block of PC1 as well as first as well as second block of PC2. The cluster of ethanol gas (E1, E2, E3) lies in fourth and fifth block of PC1 and first block of PC2. The clusters of propane gas covering in six and seven block of PC1 and first and second block of PC2. So that according to the score plot (Figure 8(a)), the detection of acetone and propane is good, detection of propane and ethanol is good and acetone and ethanol is also good. In loading plot Figure 8(b) all three sensors are distinct from each other so they can detect all gases in well manner. Figure 8(c) show the explained variance plot on the basis of score and loading plot which gives the value for PC1 is 51.3 and for PC2 is 52 and for cross validation PC1 is 47.9 and PC2 are 48.8.



(a) (b) (c)

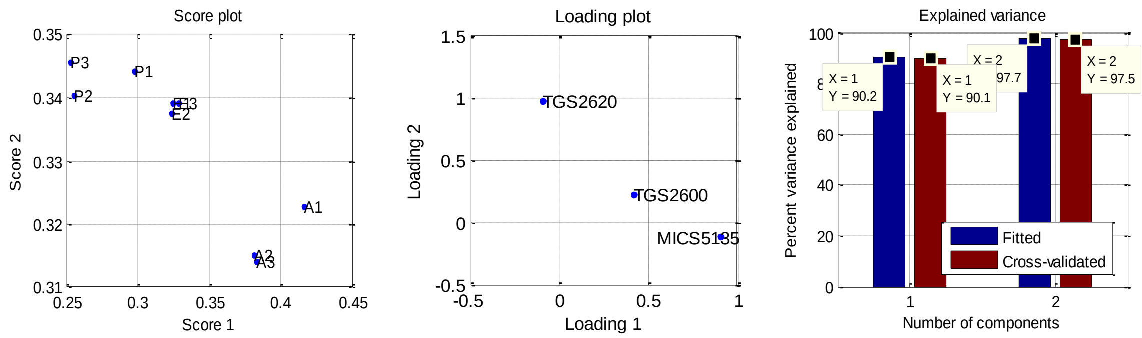
Figure 8. The score, loading and explained variance plot: (a) score plot for ANN (M2T2T4), (b) loading plot for ANN (M2T2T4), and (c) explained variance plot for ANN (M2T2T4) with cross-validation

Here Table 2 described the results for different combinations of sensors using ANN with cross-validation which has been given below. Sensors: MICS 5521=M1, MICS 5135=M2, TGS 2602=T1, TGS 2600=T2, TGS 2611=T3, TGS 2620=T4. We use different combinations of sensors from all six sensors for detecting dangerous gases. Table 2 shows the performance of all sensor arrays in various configurations. Sensor's results are categorised as good, average and poor of any two gases on 2-dimensional principle component axes as determined by ANN analysis. The smallest variation index has been observed. For the array of devices, the variation index is found the best value for three sensors (M2, T2, T4) i.e., the value on PC1 is 51.3 and on PC2 is 52, however the value in cross-validation is 47.9 and 48.8. The array has the greatest performance in three sensor sets (M2T2T4). Through the score plots, it demonstrates good segmentation in AP, PE, and EA Figure 8. As a result, the best sensor set is a three-sensor array called M2T2T4. As a result, it confirms that a huge number of sensor arrays are not required to achieve improved precision. Even a small number of sensor arrays can boost the performance.

Table 2. Results for the different combinations of sensors using ANN with cross-validation

S.N.	Sensors	Acetone and Propane	Propane and Ethanol	Ethanol and Acetone	PC1 Value	PC2 Value	Cross Validation PC1	Cross Validation PC2
1	M1M2T1T2T3T4	Good	Average	Poor	69	70	65	66.1
2	M1M2T1T2T3	Good	Average	Average	67.1	68	63	64.1
3	M1M2T1T2	Good	Good	Average	65.1	66	61	62.1
4	M2T2T4	Good	Good	Good	51.3	52	47.9	48.8

Figure 9 includes the score, loading as well as explained variance plot for PARAFAC technique. Figure 9(a) defines for three sensors MICS 5135, TGS 2600 as well as TGS 2620 (M2T2T4). In Figure 9(a) acetone gas lies in the first as well as second block of PC1 as well as third and fourth block of PC2. The cluster of ethanol gas (E1, E2, E3) lies in third block of PC1 and second block of PC2. The propane gases covering in fourth block of PC1 as well as first as well as second block of PC2. So that according to the score plot (Figure 9(a)), the detection of acetone and propane is average, detection of propane and ethanol is poor and acetone and ethanol is also poor. In loading plot i.e. Figure 9(b) all three sensors are distinct from each other so they can detect all gases in well manner. Figure 9(c) show the explained variance plot on the basis of score and loading plot which gives the value for PC1 is 90.2 and for PC2 is 97.7 and for cross validation PC1 is 90.1 and PC2 are 97.5.



(a) (b) (c)

Figure 9. The score, loading as well as explained variance plot: (a) score plot for PARAFAC (M2T2T4), (b) loading plot for PARAFAC (M2T2T4), and (c) explained variance plot for PARAFAC (M2T2T4) with cross-validation

The Table 3 shows the results of three sensors (M2, T2, T4) using PARAFAC with cross-validation. Using score plot this is showing poor classification in PE and average for AP and EA. For three sensors (M2, T2, T4) that is the value on PC1 is 90.2 and on PC2 is 97.7 but in cross-validation value for PC1 is 90.1 and for PC2 is 97.5. This table result is used for the comparison with ANN result for best sensors set that is array of three sensors. So, it is shown the results of variance for three sensors that ANN techniques have better results compare to PARAFAC results.

Table 3. PARAFAC result for three sensors with cross-validation

S.N.	Sensors	Acetone and Propane	Propane and Ethanol	Ethanol and Acetone	PC1 Value	PC2 Value	Cross Validation PC1	Cross Validation PC2
1	M2T2T4	Average	Poor	Average	90.2	97.7	90.1	97.5

5. CONCLUSION

In this research, we created an odour monitoring system that used an ANN and parallel factor analysis technique to improve pattern recognition and a MOS gas sensor array to identify dangerous chemicals and environmental dangers. The suggested system is a smart odour monitoring system that can detect a variety of scents that can develop in dangerous conditions. We use different combinations of sensors from all six sensors to detect dangerous gases. The outcomes of the sensors are characterized as good, average and poor for any two gases on 2-dimensional principle component axes as seen in ANN analysis score plot. The smallest variation index has been observed. For the sensor's array the variation index is found to be an excellent value for 3- sensors (M2,T2,T4), i.e., the variance value for PC1 without cross-validation is 51.3 and for PC2 is 52, and the variance value for PC1 with cross-validation is 47.9 and for PC2 is 48.8. With cross-validation, the array (M2T2T4) had the best performance in three sensor sets. Through plotting, it demonstrates good classification in AP, PE, as well as EA. As a result, the best sensor set is a three-sensor array called M2T2T4. As a result, it confirms that a large number of sensor arrays are not required to achieve improved precision. Even a small number of sensors can boost performance. However, when comparing principle component analysis PARAFAC with and without cross validation for the similar sensor set, detection of gases is low and average for all gases (M2T2T4). The value for three sensors (M2, T2, and T4) is 90.2 on PC1 and 97.7 on PC2, yet the value in cross-validation is 90.1 on PC1 and 97.5 on PC2. As a result, it is evident that the sensor array's performance improves as the variation decreases. When compared to PARAFAC, the results obtained with ANN exhibit less volatility. So, with the same sensor set, ANN is better than PARAFAC.

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