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An Approach to Non Invasive Neural Network based Diagnostics of Asthma using Gas Sensors Array

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Abstract

Objectives: This paper presents a neural network based non-invasive diagnostics methodology of asthma using gas sensors array working as artificial olfactory. **Methods/Statistical Analysis**: A series of invasive clinical trials are recommended by international bodies to justify the diagnosis of asthma. So during these tests the patient has to undergo a lot of physical trauma. To ease the suffering of the patient, in this paper, a non-invasive method for asthma detection has been proposed. **Findings**: In this paper, an array consisting of five semiconductor gas sensors has been developed. The sensor array along with the data acquisition system has been developed for the non-invasive detection of the asthma. Five data sets of asthma related toxic gas in different concentrations are obtained by a signal acquirement system having tin oxide gas sensor array. Obtained data are put for training and analysis on Artificial Neural Network (ANN). Proposed neural network has been trained using back propagation algorithm. From the results obtained, it can be seen that the developed model ensures the proper accuracy and consistent results. **Application/Improvements:** Experimental results show good classification of asthma associated exhaled toxic gas with the ambient air using only few samples and also presents the efficiency of Feed Forward Back Propagation Neural Network on the data driven from different gas sensors.

Keywords: Asthma, Electronic Nose, Neural Networks, Non-invasive Detection

1. Introduction

Bronchial asthma is common health disorder which has engulfed people of several age groups globally. The concentration of Nitrogen Oxide (NO) in the patient is widely used as a benchmark for asthma diagnosis. People suffering from asthma have higher concentrations of NO in their breath samples as compared to a non-asthmatic and the levels of NO to vary with diseases[1]. Finding of asthma is based on medical record, shortness of inhalation and cough that vary with seriousness and over time[2]. Sputum smear laboratory test, blood test, spirometery or 3 types of skin tests; 1. Prick test, 2. Scratch test and 3. Intradermal test when asthma is triggered by an allergy, are some traditional non-invasive method to diagnose the asthma. Breathed out NO is alluring biomarker as the test is totally non-intrusive, the cost per test is low and the outcome is immediate[3].

As application of NO measurement develops for diagnose of asthma, the need for cheap and easy to use technologies for clinics and patients home should be addressed. This must include portability, simplicity, suitability for remote locations and lack of need to calibrate. A sensor array for the detection of exhaled toxic gases (NO) can play a vital role in easy diagnosis of asthma. The prime defiance is in the characterization of gas because of poor preference of sensing instruments as they have cross affectability to different gasses. By using a set of different sensors, we can improve the selectivity[4]. The feedback produced by cluster of sensors prompts to a specific and interesting example of response after which the characterization should be possible by exerting different Pattern Recognition (PR) strategies[5]. The Pattern Recognition is a procedure to identify test samples by perceiving certain examples in the element space of the sensor cluster feedback signals. Fourier transform techniques[6], Transformed

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Cluster Analysis (TCA)[7], minimum difference method[8], are some of the established PR techniques but are limited by computational memory, time and nonlinear transduction property of sensors[4]. Pattern Recognition using ANN has the potential to adapt, master, generalize, organize the data and capable to address nonlinear transduction properties of sensor array. The proposed work has the faithful detection of prime biomarker of asthma i.e. Nitric Oxide using the gas sensor array and Artificial Neural Network.

The present paper is organised into following four sections. Section 1 presents background to diseases, the theory of sensors and back propagation algorithm Section 2 describes the experimental setup and in Section 3 results have been discussed followed by conclusions in Section 4.

2.1 Asthma

Asthma (AZ-ma) is an inflammatory chronic (long-term) respiratory disease characterized by a variable airflow obstruction in which the affected subjects usually present wheezing, shortness of breath, cough and/or tightness of chest. Asthma is a common disorder affecting approximately between two to twelve percent of people worldwide. Its prevalence varies substantially across the different countries and seems to have been increasing during the last decades.

Asthma is a global health concern as it has engulfed people of several age groups (but it most often starts in childhood) and affects their physical, emotional and social life. Globally around 300 million people are asthmatic. The commonness of asthma increments as groups receives present day ways of life and gets to be distinctly urbanized. With the extent of the total populace living in urban territories anticipated to increment from 45 to 59 % in 2025, there is probably going to be a checked increment in the quantity of individuals with asthma worldwide throughout the following two decades. It is evaluated that there might be an extra 100 million individuals with asthma by 2025. Various research centers show that Nitric Oxide (NO) and Carbon Monoxide (CO) exist together in the human respiratory routes both in wellbeing and sickness[9]. Estimations of respiratory route determined demonstrate that NO and CO is discharged at various levels in the respiratory framework in wellbeing and illness. Breathed out NO is elevated in asthma[9] and proposals have been made that this non-intrusive test can be utilized to screen respiratory routes irritation. In healthy subjects NO discharge in the lower respiratory routes is for the most part low[10].

Lately, there have been a few reports on expanded levels of breathed out Carbon Monoxide (CO) in patients with asthma[6].

Nitric Oxide (NO) and Carbon Monoxide (CO) have gotten a great deal of consideration over the previous decade. Interestingly, elevated amounts of NO are found in the nasal respiratory routes of sound subjects. Parts of the NO found in nasally determined air is delivered in the standard nasal sinuses, where a high-rate creating inducible NO unions is continually communicated. Moreover, it has additionally been recommended that CO is discharged in the nose and paranasal sinuses of healthy individuals. Accordingly, it appears as if NO and CO exists together in the aviation routes both in healthy and sick beings. In spite of the several studies taking a gander at the respiratory route arrival of NO or CO there have been few endeavors to gauge both gasses all the while in solid subjects utilizing institutionalized systems. Moreover, breathed out CO and NO are expanded in patients with aviation routes irritation or asthma. Estimation of breathed out Nitric Oxide (NO) is a generally basic, reproducible non-intrusive test for checking endogenous inflammations in asthma.

Breathed out Nitric Oxide (NO) has attracted in huge enthusiasm as a non-invasive marker of respiratory route aggravation. The motive for this study was to figure out if breathed out NO in subjects with asthma differed by atopic status and to look at its relationship with respiratory route hyper responsiveness and lung function estimations. Forty patients with asthma and 13 controls took part in the review. Nitric Oxide was measured on three events with interims of no less than 3 days, utilizing a chemiluminescence strategy. It has been watched that, atopic subjects with asthma had larger amounts of breathed out NO than non-atopic subjects. Atopic status ought to be considered when measuring levels of breathed out NO in subjects with asthma. Additionally the measure of CO has some expanded level in the breathed out gasses[9].

All the above methods for the diagnosis of asthma are invasive in nature as they commonly include prick test and scratch test. There is one test that helps a specialist analyze asthma and it is truly simple to do. The specialist will give you a peak stream meter. This is a hand held gadget that measures how you breathe. You will play out this test with no drug and your outcomes will be recorded[11]. At that

point, you will be given a prescription that is intended to open your respiratory route. On the off chance that you can breathe out better after the solution is given than you could before then more than likely you are determined to have asthma. Ordinarily specialists will likewise prescribe sensitivity testing and CT sweeps or X beams of the trunk to preclude whatever other issues[12].

2.2 Conduction Process in Tin Oxide based Sensor

For detecting gases like Carbon Monoxide (CO), Carbon Dioxide (CO_2), Nitric Oxide (NO_X) Methane (CH_4) and organic vapours thick – film gas sensors are preferred. These thick film sensors are made up of tin-oxide film (SnO_2), iron oxide, zinc oxide, etc[13]. Tin oxide is generally utilized for gas sensing instruments because of its ability to detect different gases.

A wide film SnO_2 gas sensor works on the standard of progress in transmission because of the chemisorptions of gas particles on the sensor facade. Chemisorptions is an irreversible adsorption process by means of chemical instead of physical and the existence of substance at a surface in a different concentration than in the adjoining bulk is called adsorption[14]. Different representations have been suggested to perceive the working of SnO_2. Morrison presented an experimental association between the susceptivity and concentration of test gas. In[15] suggested a non-linear dispersion reaction guide for the differences in the conductivity. Followed by Geistlinger who suggested chemisorptions based infinitesimal prototype for wide-film gas sensors. As of late the electrical conductance in SnO_2 is expected to the non–stoichiometric creation thus of O_2 insufficiency. A wide film of SnO_2 is as countless that are in exposure at their limits. The electrical conduct of such a material with dynamic grain limits is represented by the arrangement of two-fold Schottky potential boundaries at the junction between adjoining molecules. This development is the after effect of charge catching at interface. Trap states introduce at these interfaces can catch lion's share transporters. So bowing of the band happens, shaping a boundary at the junction. The stature of this hindrance controls the conductivity. It has been accounted for before that when the width of the grains is much bigger than 2L (L is Debye length), then the conduction is for the most part due to the Schottky – obstruction demonstrate. Here it has been accepted that the general conductivity is controlled by vast molecules with measurement more prominent than 2L.

At the point when the SnO_2 facet is set in an air encompassing, O_2 atoms are adsorbed at the surface. The adsorb O_2 acknowledges electrons from the snare condition show at the intercession of neighbouring molecules to shape O_2, O, O_2 ions, in this way diminishing the grouping of the quantity of charge transporters close to the surface and offering ascend to a lessening gas, the CO absorption and shared communication between the reactants (decreasing gas e.g. CO, CO_2, NO_x and O_2 gas) result in oxidation of lessening gas at the surface. This oxidation marvel helps in the expulsion of oxygen particles from the SnO_2 surface, bringing about an abatement of boundary tallness and accordingly expanding the conductance.

Utilizing Schottky boundary conduction mechanism across molecule limits and the Freundlich absorption isotherm, a correlation between conductivity G and the density of gas C was acquired[14] and the last expression is as per the following:

$$G = G_0 \ \exp(B'C^{b'}) \tag{1}$$

Where G_0 is the conductivity of receptor without the presence of trial gas:

$$B' = \frac{e^2\alpha^2R^2a^2}{2\varepsilon\varepsilon_0 k} N_S T \exp\frac{[-2\Delta E/KT]}{N_D} \tag{2}$$

Where
α and R are fixed variables;
N_s is no. of surface charge/section.
N_D is no. of ionized contributor state/volume.
ε^0 is the permittivity of the free space.
ε is the permittivity of the semiconductor:
C is desnity of the trial gas.
b' is absorption isotherm constant,
K is the Boltzmann constant and
T is the temperature.

The model has been made more comprehensible to ease the process of data validation:

$$\frac{G}{G_0} = \exp[B'C^{b'}] \tag{3}$$

Applying logarithm to Equation 3, we get:

$$\log\frac{G}{G_0} = B'C^{b'} \tag{4}$$

Taking the log of the Equation 4, we get,

$$\log\left[\log\left(\frac{G}{G_0}\right)\right] = \log B' + b'\log C \tag{5}$$

Now it can be seen Equation (5) that a graph between log [log (G/G_0) and log C is linear with gradient b' and intercept log B'. The constant b' is a constant non-dependent on temperature while constant B' depends on temperature[14].

Absorption of the gas on the sensor's surface results in the variations in resistivity of the sensor's material. If the gas under consideration is a reducing gas, then it produces the tethered electrons and thus reduces the resistance of the area. The change in the resistance, the sensitivity is as:

$$S = \frac{(R_a - R_g)}{R_a} * 100\%$$

Where, R_a and R_g are resistance of sensor in clean air and in presence of gas respectively with different concentration of organic vapour.

2.3 Back Propagation Algorithm

2.3.1 Initialization of Weights

Initially, the NN weights and nodes are set to tiny random values. Here the hub edge is the negative of the weight from the predisposition unit (whose activation level is fixed at 1).

Activation Function

- The initiation rank of info component is controlled by case displayed to system.
- Equation below gives the activation level O_j of a hidden and output neurons as:

$$O_j = F(\sum W_j O_i - \theta_j)$$

Where W_{ji} the weight from an input is O_j, is the node threshold, and F is sigmoid function:

$$F(a) = \frac{1}{1 + \exp(-a)}$$

Weight Tuning:

- Initially at O/p unit, alter weights as:

$$W_{ji}(t+1) = W_{ji}(t) + \Delta W_{ji}$$

Where W_{ji} is the weight from i to j at t time and W_{ji} is the weight adaptation.

- The change in weight is computed by

$$\Delta W_{ji} = \eta \delta_j O_i$$

Where η is a learning speed (0<η<1) and δ_j is the error derivative at j.

Merging is some of the time speedier by including a force term:

$$W_{ji}(t+1) = W_{ji}(t) + \eta \delta_j O_i + \alpha[W_{ji}(t) - W_{ji}(t-1)]$$

Where 0<α<1 (α is momentum term).

- The error gradient is given by:

For the output Unit:

$$\delta_j = O_j(1 - O_j)(T_j - O_j)$$

Where T_j is the target results and
O_j is the actual result at output unit j.
For unseen units:

$$\delta_j = O_j(1 - O_j)\sum \delta_k W_{kj}$$

Where δ_k is gradient mistake at unit k to which a link point from hidden j.

- Repeat iteration till convergence is obtained by:

$$E = \frac{1}{2}\frac{\sum_{i=1}^{n}[\sum_{j=1}^{m}|(T_{ij} - O_j)|]^2}{n}$$

Where m is no. of output units and n is total no. of input samples.

The title «back propagation» originates from the way that the mistake (angle) of concealed unit is gotten from proliferating in reverse the blunders connected with yield units since the objective qualities for the shrouded units are not given.

At the point when a flag of gas/scent 1 comes, the system is prepared so that the yield unit 1 reacts firmly and the other yield unit ways to deal with zero esteem (i.e. try not to respond to this gas/scent) i.e. A neuron comparing to a specific gas test class should fire at an esteem relating to the specific fixation band to which the test had a place, while every single other neuron should be deactivated. Thus the system is prepared for different gas/smell. Subsequent to preparing, the obscure information design (i.e. at the point when the sort of gas/smell and its focus are not known) can be recognized by this system utilizing the beforehand learnt information set[16].

3. Experimental Results and Discussion

3.1 Detection of NO_x

Gas detecting investigations were completed in a static framework outfitted with warming facilities. The detect-

ing attributes were measured under a controlled test gas/vapor atmosphere, made by presenting a known amount of gas into the chamber. To get the improved and best input results for the artificial neural network, an array of five different semiconductors gas sensors (with different sensitivity and selectivity) of Figaro Corporation in Japan were used instead of fabricated gas sensors. The array of sensors designed by commercial models of gas sensor TGS2610, TGS822, TGS2611, TGS2620 and TGS825 is shown in Figure 1.

The individual sensor needs 2 voltage references. Radiator voltage (V_H) and circuit voltage (V_c). The radiator voltage is connected to incorporated warmer with a specific end goal to keep up the detecting component at particular temperature ideal for detection. Circuit voltage is connected to permit estimation of voltage (V_{RL}) over heap resistor (R_L) which is associated in arrangement with sensor.

The experimental values taken for the measuring circuit are as follows in Figure 2:

V_H, V_C, = 5V (DC)

R_L= 1KΩ

Sensor devices were pre-annealed at desired temperature with integrated heater for 10 minutes in air prior to sensitivity or resistance measurement to stabilize the sensor. A settled amount of NO_x and CO was infused into the chamber through a small scale syringe. The detecting attributes were examined at any rate for three specimens combined under indistinguishable test. The voltage of source resistor R_L associated constantly with the sensor. The voltage in ambient air, in the presence of NO_x and CO was observed across reference resistor with help of digital multimeter (Kiethly2000) and data was recorded in computer in excel data sheet. The higher voltage demonstrates the lower resistance of the sensor in test gas surrounding.

Graph in Figure 3 shows the variation of voltages across R_L in the presence of ambient air. As it is evident from figure that all the sensors present in the sensor array shows the saturation level for ambient air. When 1 ml Nitric Oxide introduced in the test chamber all the sensors represent some variation in the voltage across R_L according to their sensitivity as shown in Figure 4. Sensor TGS825 shows more sensitivity for the experimental gas in comparison to other sensors.

The corresponding percentage change in resistance (Sensor resistance (R_S) is using: $R_S = [(V_C * R_L)/Vout] - R_L$) is represented in Figure 5.

Figures 6 and 7 shows the change in resistances of sensors for 2 ml and 3 ml concentration of Nitric Oxide respectively. It can be observed from the above graphs for the different concentration of Nitric Oxide all the sensors show some sensitivity. Some sensors show more sensitivity and some sensors less and thus produce a highly correlated and nonlinear data.

Figure 1. Sensor array used for detection of toxic gases.

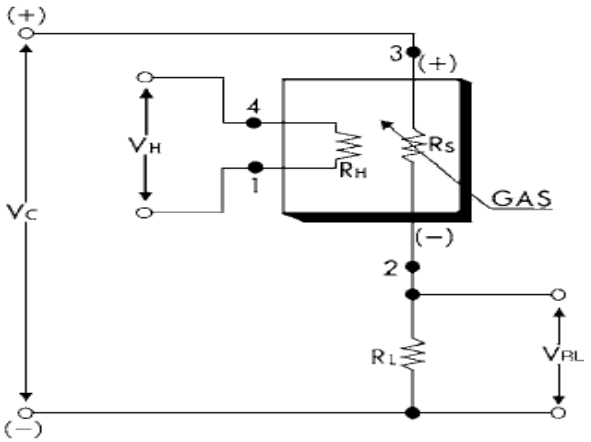

Figure 2. Basic measuring circuit of an individual sensor.

3.2 Ambient Air and Different Concentration of NO_x (Application of Neural Network for Discrimination of NO_x)

The technique of ANN has been applied to the experimental data set obtained from fabricated gas sensors array. The responses (in terms of % change in resistance) of senor array for ambient air and for different concentration of NO_x gas at have been used as training mode (input) data set. A solitary concealed layer feed forward

ANN was prepared with back propagation algorithm. The info layer comprised of five neurons and no. of neurons in the shrouded layer is enhanced by trials. The input data set were distinguished in training (learning the network) and sniffing (i.e. when the type of gas/odour is not known) data matrices. In training mode, network was trained on 4 samples (1 sample of ambient air, 3 samples of 1 ml, 2 ml, 3 ml of NO_x showing different tentative levels of asthma) and tested with the other samples (at other concentrations) of gases in sniffing mode.

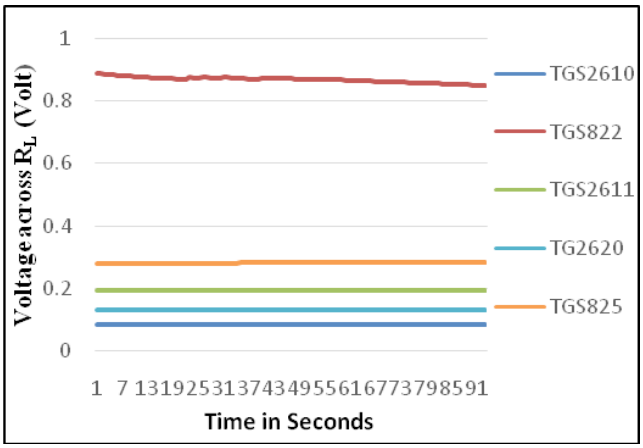

Figure 3. Variation of voltages across R_L in the ambient air.

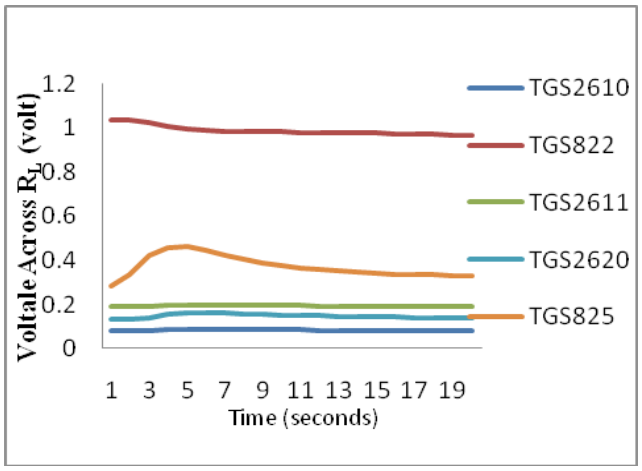

Figure 4. Variation of voltage across R_L for 1 ml No_x.

Table 1 show the input and preferred output of the network is shown in Table 2. Training data is a 5 x 16 matrix, while test data is a 5 x 4 matrix. Similarly, the output data consisted training and testing matrices of 4 x 16 and 4 x 4 dimension respectively. The design and testing has been done in MATLAB and following different types of back propagation algorithm available[17] were tried out. Figure 8 shows the plot for iterations used vs. no. of neurons in the hidden layers. Figure 9 shows system error for validation vs. no. of neurons in the hidden layer. Figure 10 shows system errors for training performance vs. no. of neurons in hidden layer. Figure 11 shows no. of neurons vs. time taken for training.

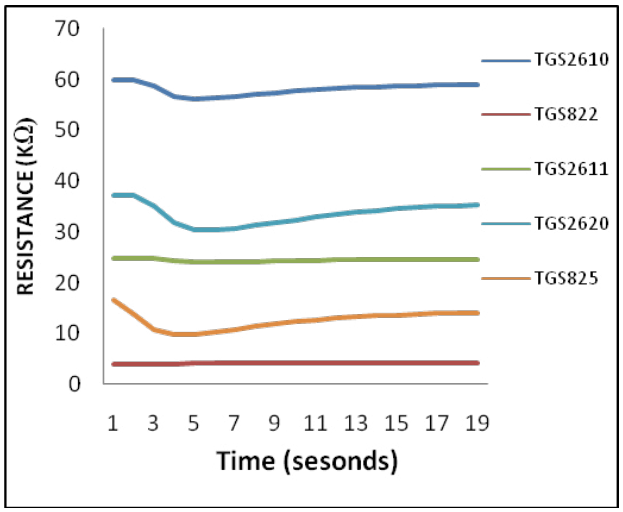

Figure 5. Change in resistance of sensors for 1 ml NO_x.

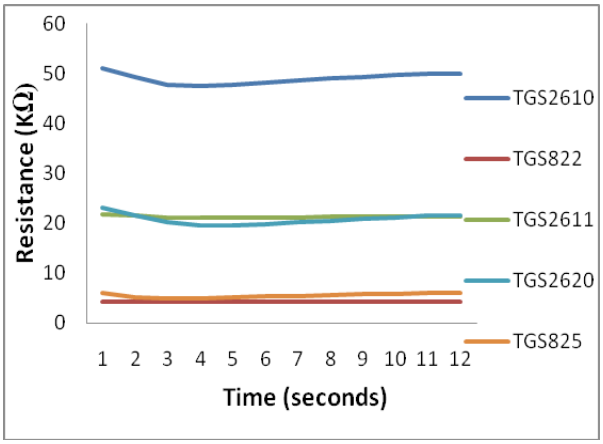

Figure 6. Change in resistance of sensors for 2 ml NO_x.

- Batch Gradient Descent Algorithm (traingd).
- Variable Learning Rate (traingda).
- Quasi-Newton Algorithm (trainbfg, trainoss).
- Gradient Descent with Momentum Algorithm (traingdm).
- Levenberg-Marquardt Algorithm (trainlm).
- Conjugate gradient Algorithm (trainscg).

Out of the distinctive training algorithms, three preparing strategies based upon back proliferation cal-

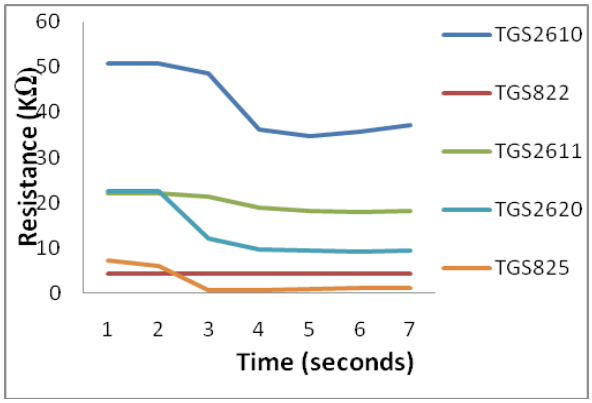

Figure 7. Change in resistance of sensors for 3 ml No_x.

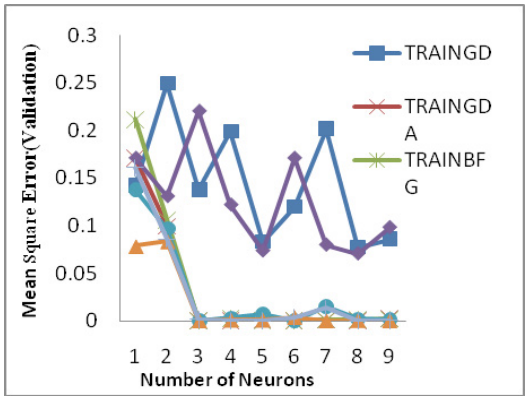

Figure 9. System error for validation vs. number of neurons in the hidden layer.

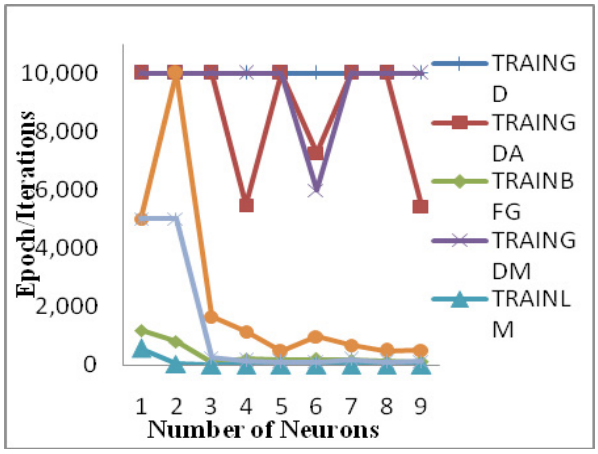

Figure 8. Iterations used vs. number of neurons in the hidden layer.

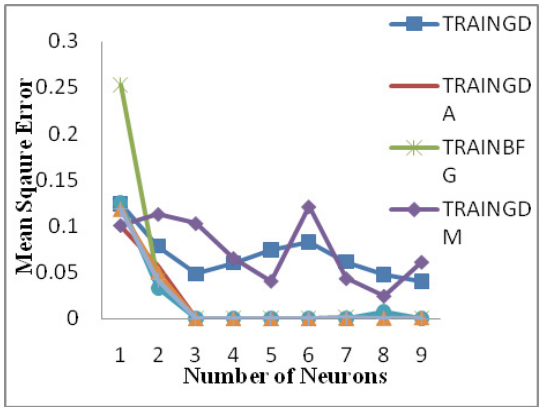

Figure 10. System errors for training performance vs. number of neurons in hidden layer.

Table 1. Data from the different sensors

	S1	S2	S3	S4	S5
AMBIENT AIR	60.01705051	4.684983523	24.8300669	37.14739801	16.84278681
	60.01271856	4.720066704	24.82953109	37.13878732	16.83110688
	60.00966566	4.782492109	24.83003063	37.14451199	16.82382187
	60.01010987	4.815858716	24.82991871	37.14987887	16.81616232
1 ml NO_x	56.72445304	4.519A847545	24.09857503	30.40986798	10.87250716
	56.22017841	4.530182776	24.06322801	30.31749547	9.938859707
	56.34250185	4.542045465	24.11221267	30.64113065	9.860529493
	56.67122921	4.550076421	24.19464209	31.14303889	10.26013479
2 ml NO_x	47.58029622	4.283761377	21.09433901	20.21233042	5.167793216
	47.82404171	4.277193753	21.07865396	19.61753433	4.95081712
	48.21486638	4.272225034	21.10173066	19.54499646	4.979428227
	48.63975142	4.293842152	21.16518519	19.80081109	5.134300069
3 ml NO_x	36.15591505	4.22585637	18.97017885	9.733360529	0.734979338
	34.68624448	4.22801527	18.2829216	9.416768708	0.794381559
	35.66810134	4.230102797	18.04221867	9.262816612	1.021675311
	37.18561362	4.231247686	18.26713328	9.491642435	1.158539307

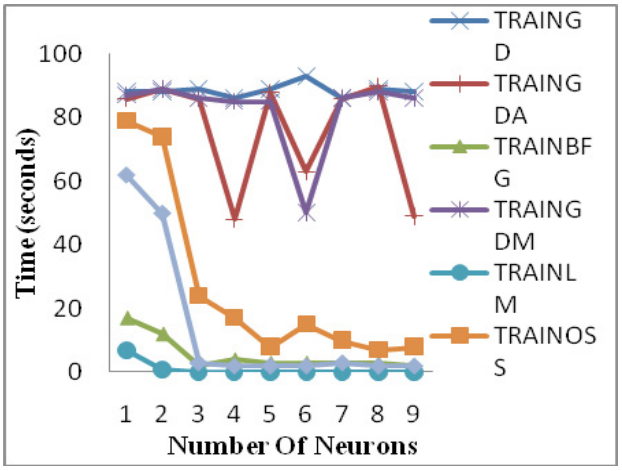

Figure 11. Number of neurons vs. time taken to train the network.

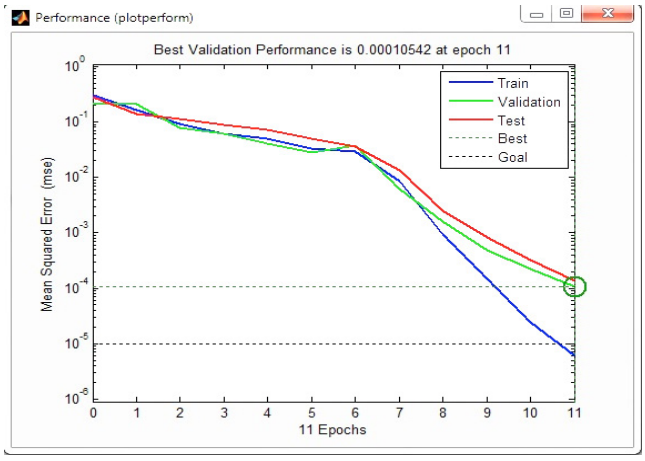

Figure 12. Mean square error for training and validation for 'trainlm' algorithm.

culation, in particular, Trainoss, Trainscg and Trainlm gave agreeable outcomes. To take out likelihood of excess fitting m-overlap cross approval conspire[18] has been utilized. For all 3 variants logsigmoidal actuation capacity is utilized. Be that as it may, they embrace diverse techniques for overhauling of weights and inclinations. Trainoss, Trainscg and Trainlm embrace 1 stage secant, scaled adjoining inclination and LM advancement techniques, separately, to overhaul weights and predispositions amid preparing[19]. The techniques depicted above have been fused in the library of MATLAB[20,21]. All the 3 preparing approaches depicted above utilize learning rate of 0.01 and default energy consistent adaptively amid re-enactment run. Total of neurons in the concealed layer of the system was differed from 1 to 9 and framework blunder (mean square mistake for preparing and approval), time taken to prepare the system and most extreme number of ages utilized was noted. What's more, delineates the adjustment in preparing stage framework blunder and approval framework mistake in quantity of neurons and from it ideal arrangement of system for each of 3 adaptations of back-propagation calculation can be ascertained[22].

Table 2. Desired output to the network

Unit 1	Unit 2	Unit 3	Unit 4
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

The no. of epochs has been limited to 10000 and an error variance of 0.00001 has been chosen. It is clear from Figure 13 that when varying the hidden layer neurons form 3 to 7 of ANN gives the minimum training inaccuracy. Hence, for training the network, hidden layer neurons varying from 3 to 5 and a learning rate of 0.01 have been selected. In the experimental stage, 04 samples of ambient air, 04 samples of 1 ml NO_x concentration, 04 samples of 2 ml NO_x concentration 04 samples of 3 ml NO_x concentration and 04 sample with 1 sample each from a certain fixed concentration band.

The proposed methods gave better learning and sniffing performance with Trainlm methodology. So, present work will discuss the Traing mode and sniffing mode only with Trainlm methodology.

Here

For ambient air	Unit 1 = 1	
For 1 ml NO_x Concentration	Unit 2 = 1	(assumed level 1 asthma)
For 2 ml NOx Concentration	Unit 3 = 1	(assumed level 2 asthma)
For 3 ml NO_x Concentration	Unit 4 = 1	(assumed level 3 asthma)

3.3 Sniffing Mode

In sniffing mode the well trained network with 'trainlm' algorithm is tested for different concentration of NO_x, and ambient air.

When the sample of ambient air is used as the unknown data, the output response of the network for ambient air became:

From Figure 14 it is clear that the output unit 1 responds strongly to the 1 (i.e. approaches to 1. While

other output units (i.e. unit 2 - unit 4) approaches to zero value (i.e. do not react to NO_x concentration group) and thus ambient air has been detected with least error. When the sample of 1 ml NO_x is used as the unknown data, the output response of the network:

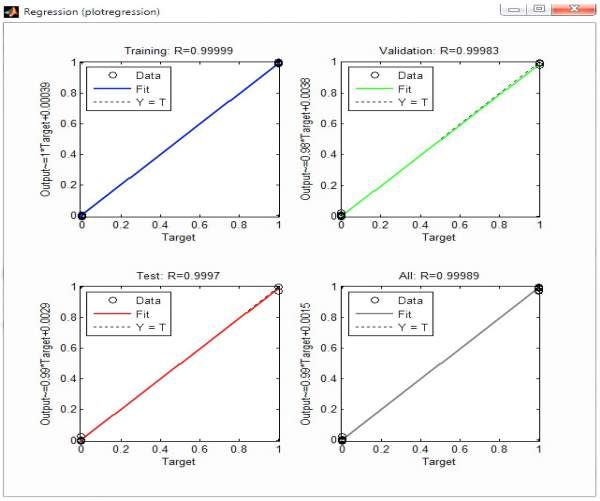

Figure 13. Regression plot for training, validation, test of network.

From Figure 15 it is clear that the output unit 1, unit 3, unit 4 responds strongly to the 0 while unit 2 approaches to one (i.e. responds to 1 ml NO_x concentration group).

Again in the sniffing mode when the sample of 2 ml NO_x is used as the unknown data, the output of the NN is shown in Figure 16.

For such type of unknown data network output belongs to the unit 3 group i.e. it approaches to 1 while the other units 1, 2, 4 approaches to zero.

For the 3 ml NOx concentration group used as the unknown data the network output follows the unit 4 is shown in Figure 17.

```
    0.9913    0.9962    1.0010    1.0023
    0.0088    0.0038   -0.0010   -0.0024
   -0.0001   -0.0000    0.0000    0.0000
    0.0000   -0.0000   -0.0000   -0.0000
```

Figure 14. Network output for the ambient air used as unknown data.

```
    0.0024   -0.0051   -0.0039    0.0038
    0.9981    1.0008    1.0014    0.9984
   -0.0005    0.0045    0.0026   -0.0022
    0.0000   -0.0001   -0.0000    0.0000
```

Figure 15. Network output for the 1 ml NO_x used as unknown data.

```
y =

   -0.0005   -0.0001   -0.0001   -0.0004
    0.0280    0.0063    0.0020    0.0245
    0.9717    0.9922    0.9996    0.9782
    0.0008    0.0017   -0.0015   -0.0023
```

Figure 16. Network output for the 2 ml NO_x used as unknown data.

```
   -0.0000   -0.0000   -0.0000   -0.0000
    0.0006    0.0008    0.0007    0.0007
    0.0034   -0.0022   -0.0020    0.0011
    0.9960    1.0015    1.0012    0.9983
```

Figure 17. Network output for the 3 ml NO_x used as unknown data.

This proves the applicability of the application of ANN to discriminate highly correlated and nonlinear data. This issue is a sensible example acknowledgment (or nonlinear discriminant examination) issue. The aim of the NN is to detect asthma is severe or not based on NO_x detection using gas sensors array.

4. Conclusion

It has been investigated that Nitric Oxide is the main and important biomarker for diagnosing asthma. The amount of exhaled Nitric Oxide by patient increases with the severity of asthma. The successful detection of Nitric Oxide in the exhaled breath using gas sensor array and discrimination of data obtained from sensors by Artificial Neural Network can provide the non-invasive approach. For diagnostic approach of asthma using sensor array, the results shows that back propagation algorithm give the best results to discriminate the NO_x from the different concentration samples of the gases mixed with ambient air.

5. References:

1. Deykin A, Massaro A., Drazen JM, Israel E. Exhaled Nitric Oxide as a diagnostic test for asthma. Am J RespirCrit Care Med. 2002; 165:1597–601.
2. Alving K, Weitzberg E, Lundberg JM. Increased amount of Nitric Oxide in exhaled air of asthmatics. European Respiratory Journal. 1993; 6(9):1368–70.
3. Leonard BI, et al. Allergy diagnostic testing: An updated practice parameter. Annals of Allergy, Asthma and Immunology. 2008; 100(3):S1–S148.

4. Francesco FD, et al. An electronic nose for odour annoyance assessment. Atmospheric Environment. 2001; 35(7):1225–34.
5. Imam SA, Khan MR. Bibliography on electronic nose and its applications. Journal of Active and Passive Electronic Devices**.** 2010; 5:1–20.
6. Nicole B, Weimar U. Understanding the fundamental principles of metal oxide based gas sensors; the example of CO sensing with SnO_2 sensors in the presence of humidity. Journal of Physics: Condensed Matter. 2003; 15(20):R813.
7. Srivastava AK. Detection of Volatile Organic Compounds (VOCs) using SnO_2 gas-sensor array and Artificial Neural Network. Sensors and Actuators B: Chemical. 2003; 96(1):24–37.
8. Machado RF, et al. Detection of lung cancer by sensor array analyses of exhaled breath. American Journal of Respiratory and Critical Care Medicine. 2005; 171(11):1286–91.
9. Cruz AA, et al. Common characteristics of upper and lower airways in rhinitis and asthma: ARIA update. Collaboration with GA2LEN. Allergy. 2007; 62(84):1–41.
10. McCormack MC, Paul LE. Making the diagnosis of asthma. Respiratory care. 2008; 53(5):583–92.
11. Hatziagorou E, Tsanakas J. Assessment of airway inflammation with exhaled NO measurement. Hippokratia. 2007; 11(2):51.
12. Heinzerling L, et al. The skin prick test – European standards. Clinical and Translational Allergy. 2013; 3(1):1.
13. Simone H. SnO_2 thick film sensors at ultimate limits: Performance at low O_2 and H_2O concentrations-Size reduction by CMOS technology. Diss Universitat Tubingen; 2002.
14. Srivastava RK, et al. Sensing mechanism in tin oxide-based thick-film gas sensors. Sensors and Actuators B: Chemical. 1994; 21(3):213–8.
15. Maeng S, et al. SnO_2 nanoslab as NO_2 sensor: Identification of the NO_2 sensing mechanism on a SnO_2 surface. ACS Applied Materials and Interfaces. 2013; 6(1):357–63.
16. Sabeur A, Fnaiech F, Najim M. A fast feed forward training algorithm using a modified form of the standard back-propagation algorithm. IEEE Transactions on Neural Networks. 2001; 12(2):424–30.
17. Kumar R, et al. A neuro-fuzzy classifier-cum-quantifier for analysis of alcohols and alcoholic beverages using responses of thick-film tin oxide gas sensor array. IEEE Sensors Journal. 2010; 10(9):1461–8.
18. Payal A, Rai CR, Reddy BVR. Analysis of some feed-forward Artificial Neural Network training algorithms for developing localization framework in Wireless Sensor Networks. Wireless Personal Communications. 2015; 82(4):2519–36.
19. Saini LM, Soni MK. Artificial Neural Network based peak load forecasting using Levenberg-Marquardt and quasi-Newton methods. IEE Proceedings-Generation, Transmission and Distribution. 2002; 149(5):5.
20. Pavani T, Das RP, Jyothi AN, Murthy ASD. Investigations on array pattern synthesis using nature inspired metaheuristic algorithms. Indian Journal of Science and Technology. 2016 Jan; 9(2). DOI:10.17485/ijst/2016/v9i2/80642.
21. Rajendran P, Thangavel D. Clustering of microarray data to identify enriched go terms of genes in severe asthma dataset using gene enrichment analy. Indian Journal of Science and Technology. 2016 Feb; 9(8). DOI:10.17485/ijst/2016/v9i8/86068.
22. Viswanadh Raviteja G, Sridevi K, Jhansi Rani A. Performance evaluation of smart antennas employing adaptive elliptical and hexagonal arrays using Particle Swarm Optimization and Genetic Algorithm. Indian Journal of Science and Technology. 2016 Jul; 9(26). DOI: 10.17485/ijst/2016/v9i26/93927.