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Resilient Back-Propagation Neural Network Based Breath Analysis System for Non-Invasive Prediction of Blood Glucose

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ABSTRACT: Diabetes is a global epidemic now with millions of people and the number is continuously on the rise. The diabetic patient has to monitor the blood glucose levels throughout the day at regular intervals of time for proper diagnostics. But, most of the blood glucose monitors present in the market are invasive and the patient has to prick the skin for collecting the blood sample. To ease this sort of suffering there is a need to develop non-invasive methods for the blood glucose detection. This paper explores the use of neural networks based upon resilient back propagation for detecting the blood glucose by monitoring the acetone levels in the breath sample. Sample hardware has been developed having several sensors for detecting the acetone levels in the breath. The developed hardware has been used in conjunction with the designed neural network for the non-invasive detection of the blood glucose.

I. INTRODUCTION

World health organization has declared diabetes as a global epidemic [1] and the numbers of diabetics have risen unusually high in last few years and by 2030 the number has been estimated to cross 522 millions [2]. For the proper diagnosis of the disease and to minimize the risk of strokes, renal function, neuropathy, etc., it is essential for the patients to monitor their blood glucose levels throughout the day. Several blood glucose monitors are available in the market. These devices use cost effective electrochemical biosensors for detecting the glucose levels in the blood. The procedure for taking the blood sample of the patient is very uncomfortable and traumatic, as the patient has to prick the fingertip throughout the day throughout the lifespan. To minimize this sort of traumatic procedure, there is a need for the development of robust non-invasive methods. These non-invasive methods offer a pain free and much simpler detection of the blood glucose levels.

In recent years, there is an increase in the non-invasive glucose monitoring devices in the market. But these devices need careful calibrations and the cost associated per test is quite high. For example, GlucoWatch© G2 Biographer [3] is a FDA approved blood glucose monitor based upon reverse iontoporesis but the major drawback with this is that it requires a warm-up time of 2-3 hours, careful calibrations, unexpected shutdowns, higher test costs etc. Another monitoring device is Pendra© is based on bio-impedance spectroscopy, one of the biggest problem with this device is that the there is a significant mismatch in reading amongst individuals and for taking the other reading the device has to be taken from the exact same spot the last reading is taken and there is a need for calibration for different skin colours [4]. There are very high precision and accurate monitors available like GlucoTrack™ [5] and TouchTrak Pro 200 by Samsung Fine Chemicals Co. Ltd. [6] but the cost factor associated with these devices is very high and the accuracy of the results is linked with the precision of the calibration.SpectRx Inc. [7] offers accuracy at par commercial analyzers and uses laser micro-precision for detection, but the device is required to be calibrated with glucose meters and there is a time lag of 2-3 minute. All these devices offers non-invasive detection of blood glucose levels but one of the major flaw with these devices is that the cost per test is very high and the accuracy of the readings is dependent on the precision of calibration.

In this paper, a non-invasive system that uses breath sample for the detection of blood glucose levels of the diabetic patients has been proposed. The breath analyzer is an array of sensors that detects the levels of acetone in the breath sample. The levels of acetone present in the breath provide the measure of level of blood glucose of the diabetic.

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Acetone present in the breath is the by-product of the breakdown of acetyl coenzyme A form the metabolism of the fatty acids [8]. In diabetics the concentration of acetone present in the breath samples ranges between 1.7 ppm to 3.7 ppm [9, 10], whereas in normal/non-diabetic person the acetone present in the breath is 0.3 to 0.9 ppm [11].The present developments in the nano-electronics and bio-sensors has made it possible to detect the concentration of gases in ppmv (parts per million by volume) and pptv (parts per trillion by volume). These nanobio-sensors are based upon the change on the conductivity cause of oxidation, and the rate of oxidation varies for different gases and metal oxide sensor used in sensor assembly.

The sensor array consists of six gas sensors and has been used as an experimental test bench for taking the breath samples. The sensor array consists of six gas sensors with varying sensitivities measures various parameters like humidity; pressure etc. and the use of varying sensitivity sensors increase the accuracy of the device. At the decision making step, to check the blood glucose levels, neural network has been designed which offers the prediction of the blood glucose levels whether they are high or not. The neural network designed here is cascade forward network type and has been trained using resilient back propagation algorithm. The main advantage offered by using resilient back propagation algorithm is that it offers faster tuning and there is no need to assign algorithm specific parameters like learning rate.

This paper has been organized into following categories. Section II gives details on the proposed hardware setup, the information on sensors used and the mechanism of experiment. Resilient back propagation has been discussed in section III. In section IV, the neural network model developed for the detection of acetone in the breath has been discussed. The results obtained have been discussed in Section V, followed by conclusions and references in section IV.

II. PROPOSED SENSOR ARRAY

A six-sensor array with varying sensitivities has been developed for detecting the acetone levels present in the breath sample. This sensor array along with the designed neural network provides the measure of the blood glucose levels of the diabetic patient. The sensor array consists of six metal oxide sensors Figaro Engineering Inc. made gas sensors. The details of the sensors are given in Table 1.

Table 1: Sensors Used in the Experimental Setup for Acetone Detection

No.	Sensor	Gases	Sensitivity
1	TGS-2610	VOCs	500-10000
2	TGS-2611	VOCs	500-10000
3	TGS-2620	ALCOHOL, SOLVENT VAPOURS.	5-5000
4	TGS-822	VOCs	5-5000
5	TGS-825	H_2S	5-100
6	TGS-816	CH_4	500-10000

Metal oxide sensors being highly sensitive are one of the best choices for such applications. The use of varying sensitivity sensors offers higher detection rates and higher degree of sensitivity. This leads to the increase in the overall precision in the detection of the blood glucose levels. The sensor array developed in this work is show in Figure 1.

Figure 1: Sensor Array used in the Experimental Setup

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The working principle of these sensors is based on the variation of their conductivity in the presence of oxidizing and reducing gases. The magnitude of the response depends on the nature and concentration of the gas and on the type of metal oxide. The basic measuring circuit for TGS 825, TGS 816 & TGS 822 is shown in Figure 2.

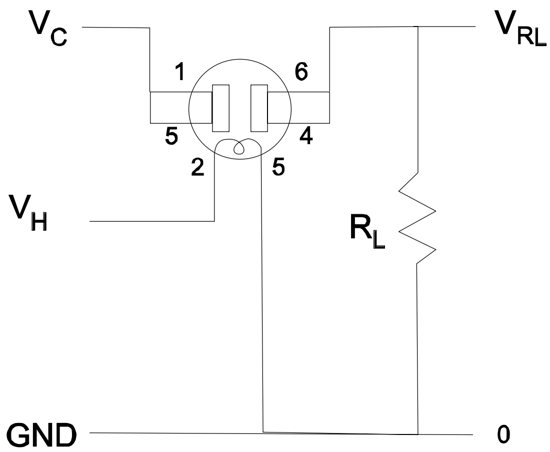

Figure 2: Measuring circuit for TGS 825, TGS 816 & TGS 822

The basic measuring circuit for TGS 2610, TGS 2611& TGS 2620 is shown in Figure 3.That the test chamber contains a sensor array, and then connects this sensor array to supply voltage of 5V and also connect the heater wire with 5V supply. The help of triple power supply i.e. Triple Power supply, HM5040 by Scientific, should give supply. The individual sensor requires two voltage inputs. Heater voltage (V_H) and circuit voltage (V_C). The heater voltage is applied to the integrated heater in order to maintain the sensing element at a specific temperature that is optimal for sensing. Circuit voltage is applied to allow measurement of voltage (V_{RL}) across a load resistor (R_L), which is connected in series with the sensor. The experimental values taken for the measuring circuit are as follows: V_H, V_C, = 5V (DC). The test chamber is shown in Figure 4.

Figure 3: Basic measuring circuit for TGS 2610, TGS 2611& TGS 2620

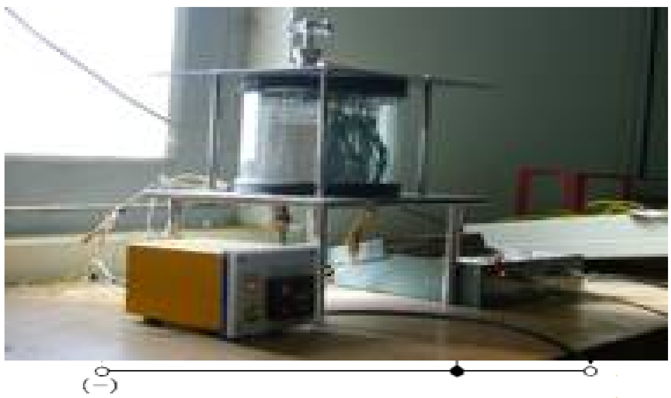

Figure 4: Test chamber for the sample collection

The test chamber is a cylindrical box contains the PCB (Printed Circuit Board) where we fixed six different types of gas sensors these are TGS 822, TGS 825, TGS 816, TGS 2620, TGS 2610, TGS 2611(Figaro Engineering Inc.). The system encompasses one input for inlet air coming from an air compressor, which has been used to clean the box and the gas sensors after each test. One output is used for the exhaust air. The amount of volatile compounds needed to create the desired concentration in the sensor chamber (our cylindrical box) was introduced in the liquid phase using a syringe. Since temperature, pressure and volume were known, the liquid needed to create the desired concentration of

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volatile species inside the box could be calculated using the ideal gas theory. The data acquisition system designed to collect samples is shown in Figure 5.

Figure 5: Data acquisition system used in the study.

III. RESILIENT BACK PROPAGATION

Resilient back propagation (Rprop) [12] has been developed by M.Riedmiller and H. Braun in 1992, is a heuristic supervised learning algorithm employed for training the feed-forward neural networks. One of the biggest advantages of Rprop algorithm is that it eliminates the effect of partial derivatives caused by squashing functions and is much faster than generic steepest descent algorithms. There's an advantage of memory associated with Rprop that one doesn't have to store the value of the updated weight and bias, instead uses thein formation of the sign of gradient for better weight updates. Rprop operates on the idea that if there is no sign change of the error gradient for a weight w_{ij} over the two epochs, it is increased by step size Δ_{ij} and to decrease the step only the sign has to be changed. Alteration in current step size changes the weights and is not dependent on the absolute value of gradient. This way the effect of partial derivatives caused by squashing functions is eliminated.

The step size rules are given as:

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^{+} \cdot \Delta_{ij}^{(t-1)}, & \text{if } \dfrac{\partial E^{(t-1)}}{\partial w_{ij}} \cdot \dfrac{\partial E^{(t)}}{\partial w_{ij}} > 0 \\ \eta^{-} \cdot \Delta_{ij}^{(t-1)}, & \text{if } \dfrac{\partial E^{(t-1)}}{\partial w_{ij}} \cdot \dfrac{\partial E^{(t)}}{\partial w_{ij}} < 0 \\ \Delta_{ij}^{(t-1)}, & \text{otherwise} \end{cases}$$

And the weight updates are performed as,

$$w_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)}, & \text{if } \dfrac{\partial E^{(t)}}{\partial w_{ij}} > 0 \\ +\Delta_{ij}^{(t)}, & \text{if } \dfrac{\partial E^{(t)}}{\partial w_{ij}} < 0 \\ 0\,, & \text{otherwise} \end{cases}$$

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IV. NEURAL NETWORK FOR DETECTION OF BLOOD GLUCOSE

To develop the neural network (NN) model for the detection of the blood glucose levels, the sample data has been taken for varying concentration of acetone. The data collected has been visualized in Figure 6. This data has been used to develop the NN based model for the breath analysis and classification whether the blood sugar levels lie within recommended levels or not. The block diagram of developed NN is shown in Figure 7.For developing the neural network model, 6 input signals and 1 output signal has been considered. The number of hidden layers have been varied, such that to find an optimal hidden layer so that we get best response. In this paper, we have used resilient back-propagation training algorithm for the modelling of the neural network. The structure of the neural network has been chosen as cascaded feed-forward configuration. The architecture is shown in Figure 7 as:

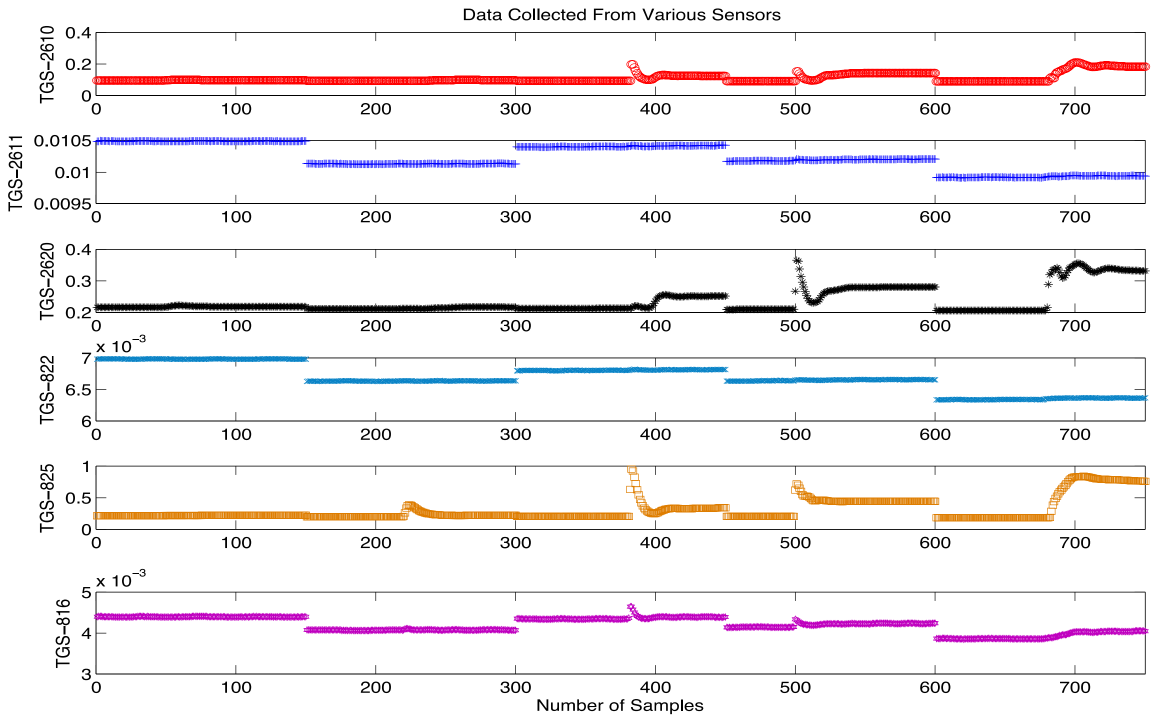

Figure 6. Visualization of the sensor data and concentration of acetone.

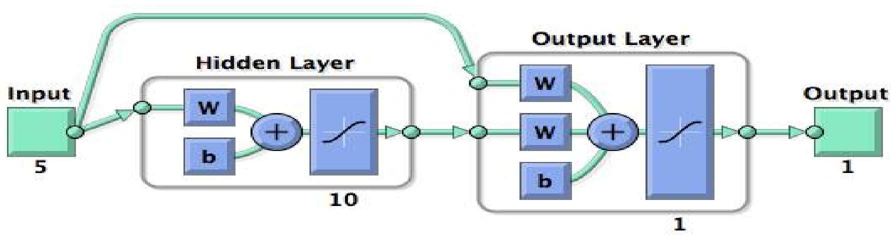

Figure 7. Block diagram of the neural network model.

V. RESULTS AND DISCUSSIONS

The resilient back propagation algorithm has been used to obtain a black box model of the proposed system. Data with acetone concentration of 0.25-5 ml has been used for developing the model. The proposed neural network has 6 inputs

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and 1 output. For obtaining the accurate estimation of acetone presence, the NN been trained for various number of hidden layer, till an optimal number of hidden layers is obtained. Performance evaluations like regression (R) have been applied to evaluation of the model. Table 2 shows the MSE for various neural networks with varying hidden layers for the training, testing and validation data. There are a total of 750 samples in the experiment and of which 70% data is used for training, 15% data for testing and 15% for validation purposes. Out of the 8 different trials to find the optimum hidden layers. As per table 2 the best response has been obtained for network with 15 hidden layers as the value of regression is close to 1. The plots for best training evaluation for 5-15-1 NN are shown in Figure 8. The plot for regression for training, testing and validation is shown in Figure 9. The plots for training slates are shown in Figure 10.

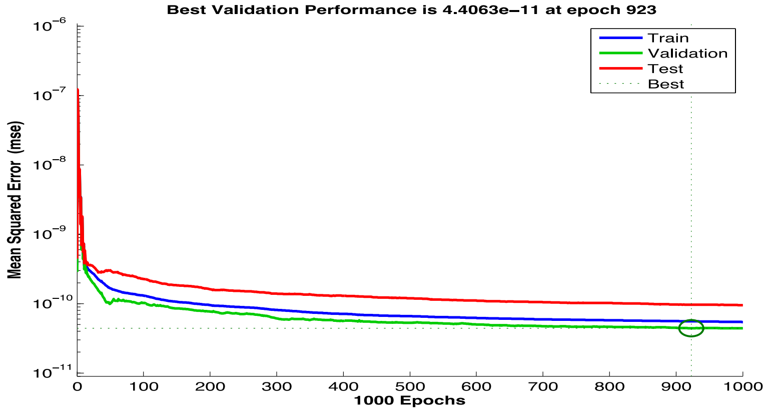

Figure 8: Plot for training of the 5-15-1 neural network

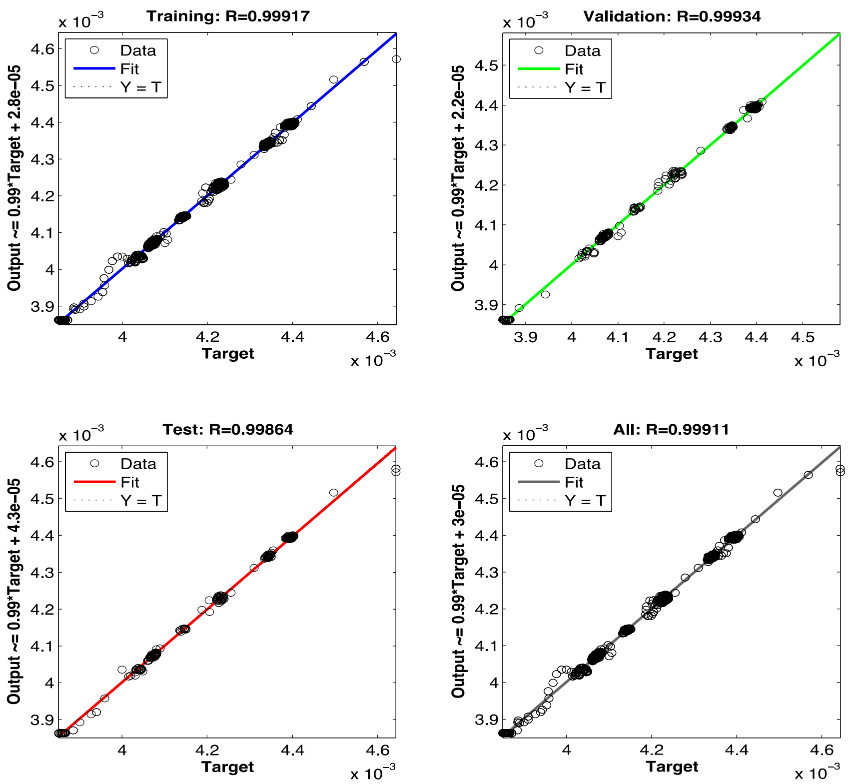

Figure 9: Plot for regression for training, testing, validation and overall of the 5-15-1 neural network.

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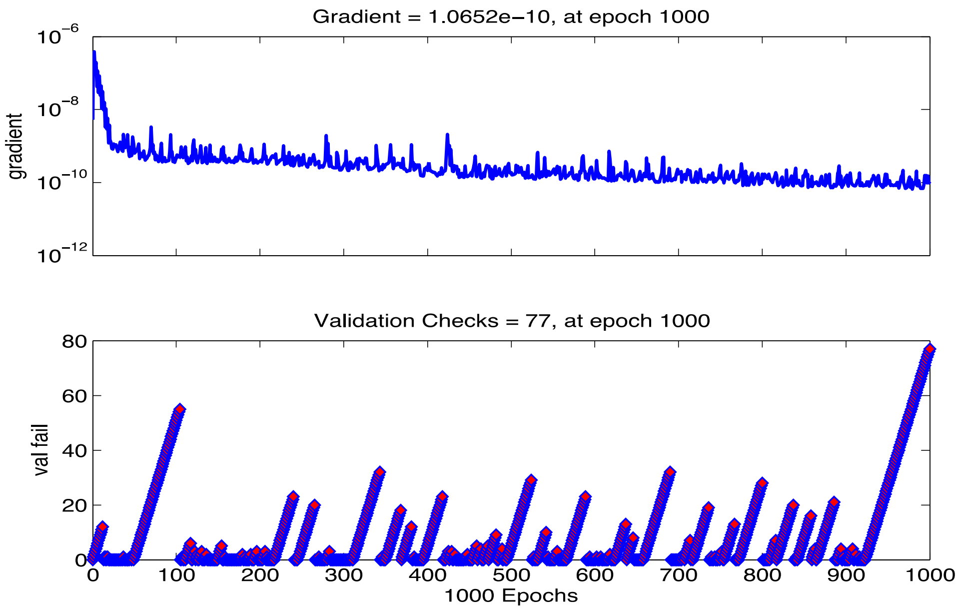

Figure 10: Plot for training states of the 5-30-1 neural network

Table 2: Performance evaluation of the designed neural network

S. No	Hidden Layers	Training Regression	Validation Regression	Testing Regression	Overall Regression
1	5-3-1	0.99637	0.99742	0.9971	0.99662
2	5-5-1	0.99846	0.99869	0.9975	0.99834
3	5-7-1	0.99731	0.99768	0.99598	0.99715
4	5-9-1	0.99567	0.99684	0.99769	0.99615
5	5-12-1	0.99726	0.99722	0.99136	0.99641
6	5-15-1	0.99917	0.99934	0.99864	0.99911
7	5-18-1	0.99887	0.99884	0.99787	0.99871
8	5-21-1	0.99652	0.99793	0.99660	0.99673

The designed network has been tested for the inputs to check the efficacy of the network. Figure 11 shows the plot between the target values and output values of the network for 0.25 ml acetone concentration.

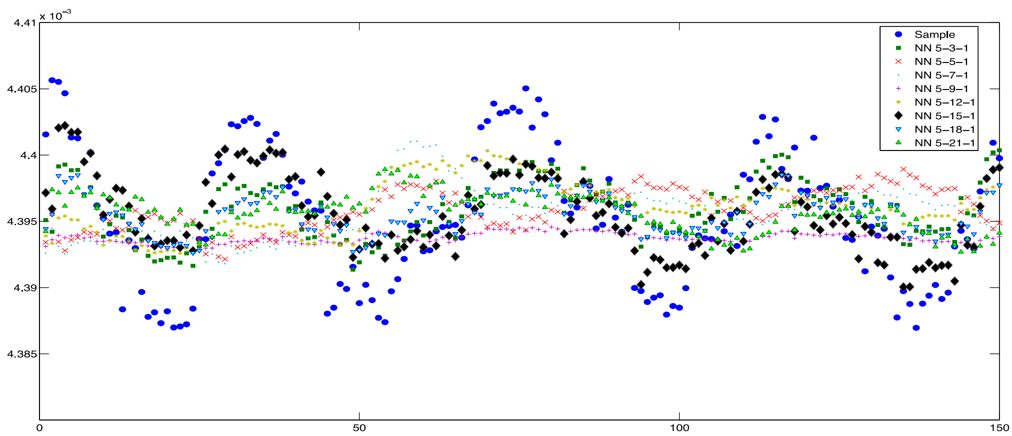

Figure 11: Compared plot for the outputs and target values of the designed NN for 0.25 ml Acetone.

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Figure 12 shows the plot between the target values and output values of the network for 0.5 ml acetone concentration.

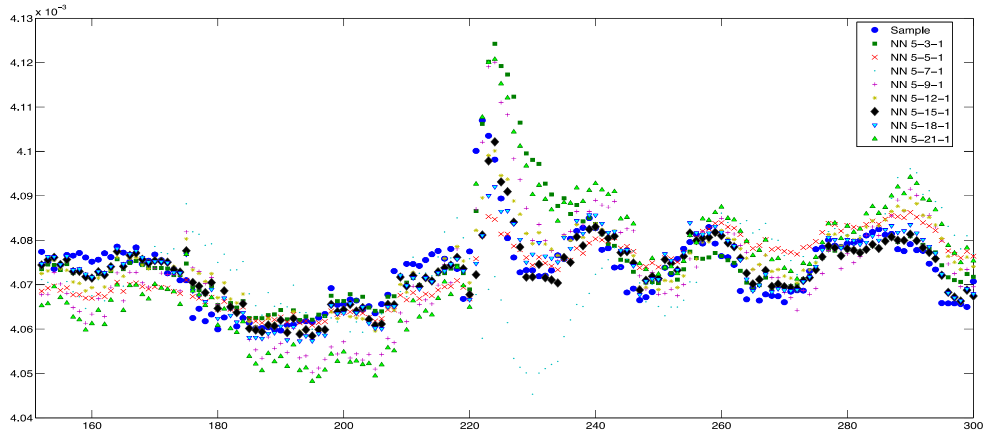

Figure 12: Compared plot for the outputs and target values of the designed NN for 0.5 ml Acetone.

Figure 13, 14 & 15 shows the plot between the target values and output values of the network for 1, 2 & 3 ml acetone concentration.

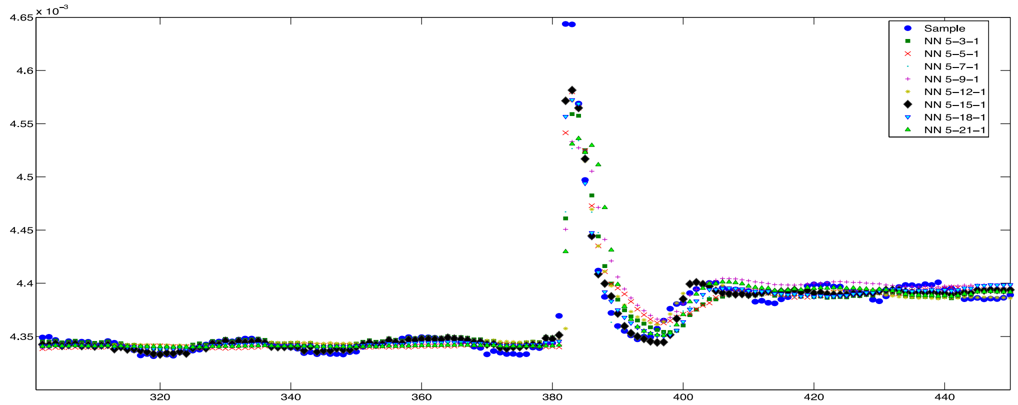

Figure 13: Compared plot for the outputs and target values of the designed NN for 1 ml Acetone.

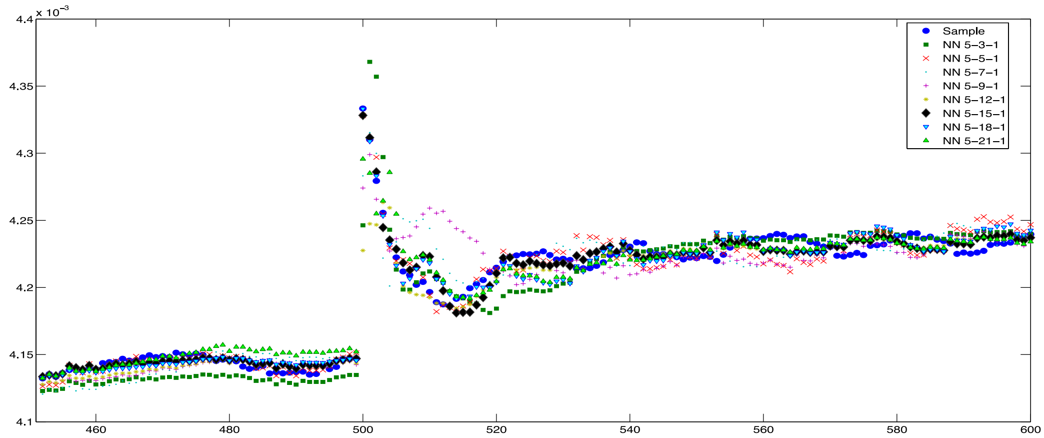

Figure 14: Compared plot for the outputs and target values of the designed NN for 2 ml Acetone.

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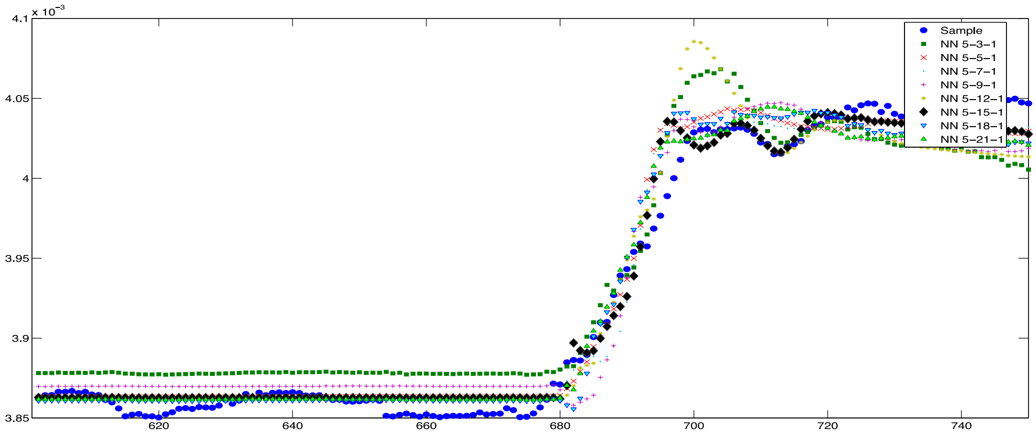

Figure 15: Compared plot for the outputs and target values of the designed NN for 3 ml Acetone.

From the above graphs and Table 2, it can be seen clearly that the designed neural network with 15 hidden layers offers the best response (form the regression values and graphically) for detecting the acetone levels in the breath sample and it can be used for the non-invasive detection of the blood glucose levels in diabetics.

VI. CONCLUSIONS

In this paper, for the detection of the blood glucose levels in the diabetics a non-invasive technique based upon neural networks has been proposed. The method uses the detection of acetone in the breath sample of the diabetic patient to estimate the blood sugar levels. The resilient back-propagation algorithm has been used for the modelling of the system and has been applied for all the acetone samples of 0.25, 0.5, 1, 2, 3 ml. The paper also studies the effect of hidden layers on the accuracy of the outputs. Varying the number of hidden layers, we have found out the best & optimal number of hidden layers has been found (a total of 8 networks have been designed). For the neural network 5-15-1, an overall regression of 0.999 has been achieved. A comparison in terms of regression has been made for all the designed 8 networks. Graphical comparison between the Outputs & Targets for all the Acetone samples has been made to aid the accuracy of the proposed technique.

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