Blood Glucose Level Measurement from Breath Analysis

Tayyab Hassan, Talha Rehman, Qasim Abdul Aziz, Ahmad Salman

Abstract—The constant monitoring of blood glucose level is necessary for maintaining health of patients and to alert medical specialists to take preemptive measures before the onset of any complication as a result of diabetes. The current clinical monitoring of blood glucose uses invasive methods repeatedly which are uncomfortable and may result in infections in diabetic patients. Several attempts have been made to develop non-invasive techniques for blood glucose measurement. In this regard, the existing methods are not reliable and are less accurate. Other approaches claiming high accuracy have not been tested on extended dataset, and thus, results are not statistically significant. It is a well-known fact that acetone concentration in breath has a direct relation with blood glucose level. In this paper, we have developed the first of its kind, reliable and high accuracy breath analyzer for non-invasive blood glucose measurement. The acetone concentration in breath was measured using MQ 138 sensor in the samples collected from local hospitals in Pakistan involving one hundred patients. The blood glucose levels of these patients are determined using conventional invasive clinical method. We propose a linear regression classifier that is trained to map breath acetone level to the collected blood glucose level achieving high accuracy.

Keywords—Blood glucose level, breath acetone concentration, diabetes, linear regression.

I. INTRODUCTION

DIABETES is one of the leading cause of death these days, affecting 8.7% percent of the global adult population [1]. It arises either due to the inability of body to produce insulin (Type-1 Diabetes) or because cells are not responsive to the insulin produced (Type-2 Diabetes) [2]. Insulin controls the glucose level in blood and inability of human body to produce sufficient insulin results in increased glucose level in blood which may prove fatal. Thus, diabetic patients are injected with insulin, and their blood glucose level is monitored regularly.

The clinical method used for measuring blood glucose level involves piercing the fingertip and collecting a large drop of blood on the test strip. It is then analyzed chemically for concentration of blood glucose. Each reading requires at least one piercing and sample collection [3]. Type-2 diabetes patients are advised to check glucose level four to seven times a day [4]. The invasive procedure is accurate, but it is painful and may cause infections and bruising. A minimally invasive glucometer was proposed in [5] that uses relatively smaller sample of blood, but its accuracy is low. Thus, there is always a need for an accurate, safe and less painful technique for blood glucose measurement.

Optical detection and spectroscopic methods for measuring blood glucose non-invasively are described in [2]. These methods utilize Light Emitting Diodes (LEDs) to measure absorption rate of a certain wavelength and are painless. However, their results are not so accurate and reliable due to variability in tissue structure under the skin for each person, and also other environmental factors [6].

A microwave frequency sensor was proposed in [7] for blood glucose measurement. A standing wave is produced on a circular spiral sensor and forward transfer function is measured when the patient places his thumb on the sensor. The limitation of this method is that it was tested on only three male and two female subjects, which is a very small sample set to validate the authenticity of technique. Secondly, during their experiments the blood glucose levels remained within normal range and they have not tested it for cases where glucose level is out of normal range.

Impedance of blood varies with glucose concentration in blood. A method based on this approach was proposed in [14]. A small current of the order of milliamperes is passed through the finger and voltage drop is measured using differential voltage meter. The results are favorable, but the hardware designed is not stable and has low accuracy as compared to invasive clinical approach.

It was observed that breath of a diabetic patient contains ketones, the concentration of which is proportional to the blood glucose level. Thus, measurement of acetone in breath can be mapped on to the blood glucose level, giving a non-invasive measurement procedure [8]. Gas chromatography is used to analyze different compounds in the breath. It is an expensive yet not portable system. Some researchers have used e-nose for classifying the breath sample as diabetic and non-diabetic, but they have not been able to determine the exact blood glucose level [12]. E-nose or electronic nose is an olfactory electronic sensor that detects odour and composition of a mixture of gases [13]. A non-invasive blood glucose monitoring for diabetics by means of breath signal analysis was proposed in [9]. The authors were able to classify the breath samples into four classes, i.e. well-controlled, somewhat controlled, poorly controlled and not controlled instead of just diabetic and non-diabetic. This method achieved an accuracy of 68.66% and thus it cannot be used for clinical practices. A system that predicts exact glucose level from breath samples was proposed in [11]. The authors trained an Artificial Neural Network (ANN) to map acetone concertation, pressure, temperature and humidity to glucose level. Their work shows promising results;

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however, the dataset used was too limited (only thirty readings) for a neural network to properly train, and thus, the results may be over-fitted to such a small dataset.

In general, the existing methods for non-invasive blood glucose measurement have three main flaws: (a) low accuracy (b) small test data with poor generalization and statistically insignificant outcome and (c), the system is not stable and is prone to environmental factors. We propose a sensor-based breath analyzer system with high accuracy and stability. A linear regression classifier is trained on data of 100 patients to map acetone concertation in breath to blood glucose level. The overall setup is shown in Fig. 1.
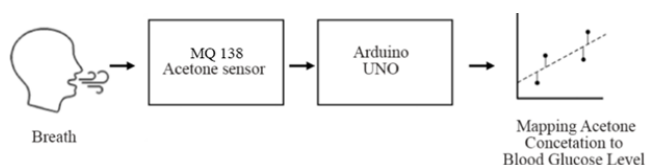

Fig. 1 Flow of proposed method

II. METHODOLOGY

The proposed system employs MQ 138 sensor which is very effective in the detection of volatile organic compounds (VOC) such as acetone, ethanol and benzene [10]. The sensor is connected to an Arduino UNO which is interfaced with LCD to show the acetone concentration in breath, which is recorded. The blood glucose level of patient is measured using clinical method. A linear regression classifier is trained to map breath acetone to blood glucose value. Fig. 2 illustrates the circuit diagram.

The circuit uses two analog sensors; temperature & humidity sensor and MQ-138 sensor for Acetone. The temperature sensor is wired to input voltage and Arduino. MQ138 has two pins for positive voltage and two for negative voltage. Another pin is connected to microcontroller through resistor. The circuit contains three push buttons, two of which are used for reset and the other one for toggling the display mode. A 16x2 LCD is used to display the sensor output. An ESP 32 Wi-Fi module is used that sends the data to the cloud web. The data can be accessed through a mobile application. The web cloud is used for Internet of Things (IoT) that helps the doctor to see patient's previous results.

MQ 138 is quite slow and may require up to 3 mins to get stable after it is powered on. The output from sensor is checked continuously at 5-ms intervals. If it remains constant over five consecutive readings, the sensor is assumed to be stabilized. The sensor has low conductivity in clean air, whereas the conductivity increases in the presence of acetone. Higher the gas concentration, lower the resistance of the sensor. The change in resistance of the sensor is mapped to the concertation of acetone in breath. The processing takes place in Arduino UNO. The pseudocode of the algorithm is summed up in Table I. The mathematical relationship used for the mapping of sensor output to acetone concertation in breath in Parts Per Million (PPM) is given below.

$$Acetone\ Concerteration = \left(-2.6 * \log\left(\frac{R}{R_0}\right) + 2.7\right)^{10}$$

where, R is the resistance measure of sensor and is constant resistance. Its value is 10 kΩ.
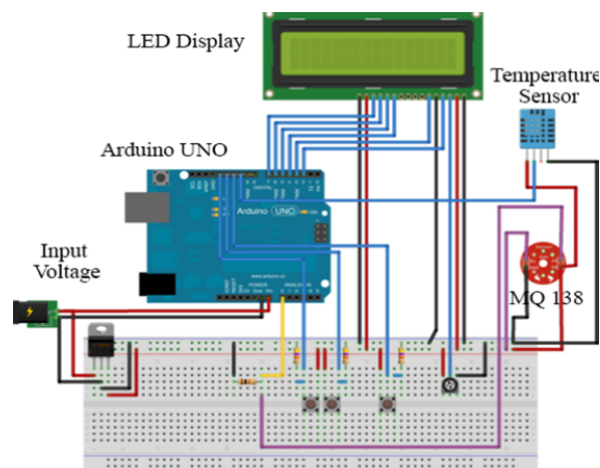

Fig. 2 Hardware schematics

Our experiment involved data collection from one hundred patients, the largest sample collected so far for the study of non-invasive glucose measuring device. A number of attributes, in addition to breath acetone and blood glucose, were recorded to increase reusability of data. A smaller set of patient information from our collected data is shown in Table II. Data collection involved following steps:

1) Patients blows into the sensor device for 10 seconds to get a stable sample.
2) Acetone concertation in breath is recorded using sensor
3) Blood glucose level is measured using the clinical method.

A mouth piece is specially designed to effectively direct the breath onto the acetone sensor MQ138. The sensor is placed inside the mouth piece. The mouth piece was 3D printed and is shown in Fig. 3.

TABLE I
ALGORITHM

Stability Check
Read sensor
Compare this reading to last two readings
    if same
        break
    else
        repeat
Recording Sensor Output
Read sensor output from the pin
Convert voltage into resistance using voltage divider
Converting resistance to acetone concentration
Convert resistance to acetone concertation using:
A = pow (10, (log10(R/R$_0$)-2.6)+2.7);*
Display Acetone concentration on attached LED

The plot of acetone concertation vs blood glucose level measured from clinical method for 100 patients is shown in Fig. 5. The dataset contains all ranges of blood glucose level. The data are split into two parts for training and testing

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purpose. Training set contains 70 readings and test set contains 30 readings.

TABLE II
SAMPLE FROM COLLECTED DATA

Age of Patient	Blood Glucose Measured from Clinical Method	Acetone Concentration in Breath	Diabetes Type
46	69.3	0.67	Type 2
48	66.6	0.6	Type 1
52	492.5	5.87	Type 2
47	296.1	2.95	Type 2
53	418.9	4.77	Type 2
55	157.8	1.77	Type 2
57	301	3	Type 2
56	203.5	2.4	Type 2
44	73.5	0.8	Type 2
45	92.8	1	Type 2
56	465.8	5.22	Type 1
57	136.8	1.3	Type 2
35	72	0.7	Type 2
52	156	1.72	Type 2
40	255	2.7	Type 2
51	73.2	0.77	Type 2
41	241	2.65	Type 2
39	188	2.1	Type 2
41	311.4	2.8	Type 2
37	136.8	1.3	Type 2
35	321.8	3.4	Type 2
44	186.9	2.05	Type 2
35	180.2	1.9	Type 2
46	69.3	0.67	Type 2
49	61.6	0.63	Type 1
51	495	5	Type 2

Fig. 3 Mouthpiece with MQ 138 sensor

To study the effectiveness of breath acetone concertation as a measure for calculating blood glucose level, a graph is plotted showing breath acetone concentration and blood glucose level measured clinically for each patient, as shown in Fig. 4. The values are normalized by their sum, so that they lie in the range 0 to 1 for comparison purpose. The graph shows a correlation of 0.92 between breath acetone and blood glucose level. This suggests a strong relationship between both quantities. Thus, breath acetone concentration can be used to estimate blood glucose level.
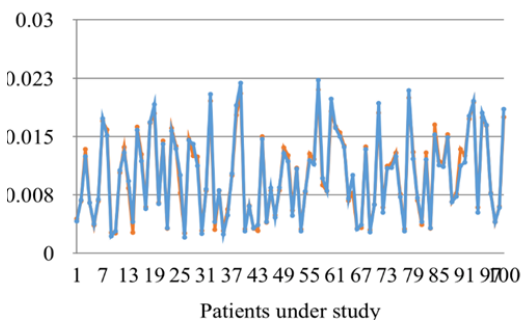

Fig. 4 Correlation between breath acetone concentrations and blood glucose level

The next step is training a classifier that can predict the value of blood glucose level given the breath acetone concentration. It can be seen that a linear relationship exists between the acetone concentration in breath and blood glucose level. Thus, following linear regression classifier was trained on training data for prediction:

$$BGL = 91.38 * AC + 6.3743$$

where BGL is the blood glucose concentration and AC is the acetone concentration in breath.
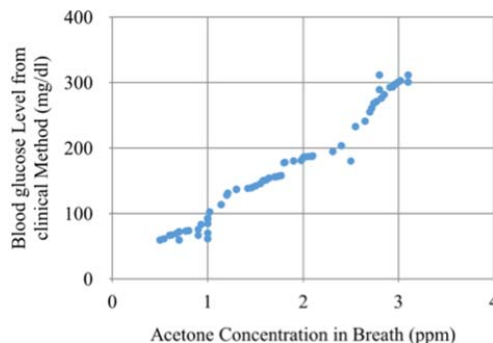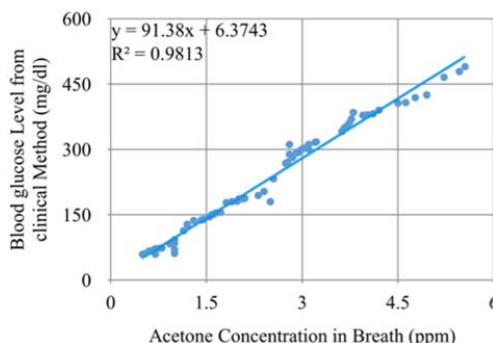

Fig. 5 Visualization of data (100 patients)

Fig. 6 Linear regression on training data

III. RESULTS

On test data of 30 readings, spanning over the entire range of glucose levels, we achieved Root Mean Square Error of

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11.81. The Root Mean Absolute Error is 3.106. The correlation coefficient between the Blood Glucose Level determined from clinical method and that from proposed method is 0.995.

$$Root\ Mean\ Square\ Error = \sqrt{\frac{(x-y)^2}{N}}$$

$$Root\ Mean\ Absolute\ Error = \sqrt{\frac{|x-y|}{N}}$$

$$Correlation\ Coef = \frac{\sum_{i=1}^{30}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{30}(x_i-\overline{x})^2 \sum_{i=1}^{30}(y_i-\overline{y})^2}}$$

where x is the glucose level determined from clinical method, y is the glucose level determined from proposed method, and are the respective mean values.

A plot of blood glucose level measured clinically and that determined from proposed method is shown in Fig. 7. It can be seen that the results of proposed method are fairly close to the clinical method. There is scope of improvement, but our approach provides basis of measuring precise glucose level from breath acetone concertation and thus providing a non-invasive technique for blood glucose measurement.
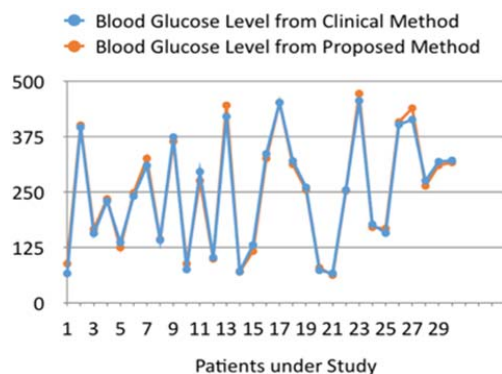

Fig. 7 Blood glucose level from clinical method vs proposed method for test data

IV. CONCLUSION

This work is a step towards the development of an IoT based non-invasive system for precise blood glucose measurement from breath acetone. The previous work for blood glucose level detection that is based on monitoring breathe acetone levels was not generalized due to its verification on small datasets. We have collected a reasonable amount of dataset comprising of patients with wide range of glucose levels. Our system is trained and tested on relatively larger dataset therefore, the results are more acceptable. The biggest challenge was making the hardware stable and resistant to environmental factors. We believe that this work provides a way forward for more and better investigation in developing non-invasive and cheaper solutions for blood glucose measurement.

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