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IoT Enabled Non-Invasive Glucose Monitoring Through Breath Acetone

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Abstract

This paper presents a non-invasive blood glucose monitoring system integrated with Internet of Things (IoT) technology using breath acetone detection. The system utilizes a TGS822 gas sensor to detect acetone levels in exhaled breath, which are correlated with blood glucose concentration. To enhance accuracy, environmental parameters such as temperature, humidity, and pressure are measured using DHT11 and BMP180 sensors. Sensor data are processed using Arduino-based signal acquisition and regression analysis techniques to estimate glucose levels, which are displayed in real-time on an LCD and transmitted for remote monitoring. Experimental validation was conducted on 11 subjects, and results demonstrated a strong correlation with standard glucometer readings, achieving an accuracy of approximately 98%. The proposed system offers a reliable, painless, and cost-effective alternative for diabetes management.

Keywords: Non-Invasive Monitoring; Blood Glucose Estimation; Breath Acetone; IoT-Based Healthcare; Gas Sensors; TGS822; Diabetes Management

1. Introduction

Diabetes is a prevalent chronic disease that affects approximately 463 million people worldwide, with projections indicating that this number could increase to 700 million by 2045 [1]. The condition results from the body's inability to regulate blood glucose levels, which, if left unmanaged, can lead to serious health complications [2, 3]. Regular monitoring of blood glucose levels is essential for people with diabetes to minimize the risk of adverse outcomes and ensure effective disease management [4, 5]. Diabetes generally presents in two main forms: Type 1 and Type 2 [6]. Type 1 diabetes is an autoimmune condition characterized by minimal or absent insulin production due to the immune system attacking insulin-producing pancreatic cells. This form typically manifests in childhood or adolescence and requires frequent blood glucose monitoring - usually four to ten times per day - and daily insulin injections [7]. In contrast, Type 2 diabetes is a metabolic disorder marked by insulin resistance or insufficient insulin production. It affects primarily adults and is often associated with lifestyle factors. Although individuals with Type 2 diabetes typically monitor their blood glucose levels one to four times a day, regular checks remain essential for effective treatment [8]. Current glucose monitoring technologies include finger-prick tests and continuous glucose monitors (CGMs). Finger-prick testing involves drawing a small blood sample multiple times a day, which can be uncomfortable and inconvenient, leading to poor compliance. CGMs, which use a sensor placed under the skin, provide more consistent readings but may also cause discomfort, require frequent replacement, and necessitate periodic calibration [9, 10].

These challenges can diminish the effectiveness of diabetes care. Thus, in the present work, a non-invasive glucose monitoring system that detects acetone in breath is proposed, integrated with Internet of Things (IoT) technology to address existing limitations. Acetone, a byproduct of fat metabolism, correlates with blood glucose levels and can be measured in exhaled breath [11]. This system offers a painless and continuous alternative to traditional finger-prick tests, enhancing comfort and convenience. It provides real-time data and alerts, enabling immediate diet, exercise, or medication adjustments. Additionally, IoT integration allows healthcare providers to remotely monitor patients' glucose levels, facilitating more informed and responsive care [12].

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2. Related Works

Malinin et al. [13] developed and evaluated a non-invasive blood glucose monitor based on bio-impedance. The study explores the basic principles of bio-impedance, its application in glucose monitoring, and the influence of frequency on impedance measurements. The average discrepancy between invasive and non-invasive readings was less than 20% for both static and dynamic testing across Type 1 and Type 2 diabetic patients, as well as healthy individuals. The system schematic includes a data processing module incorporating neural network (NN) techniques and filtering and data acquisition components. Signals from the bio-impedance sensor are processed using the AD5933 signal conditioner and an amplifier. The microcontroller LPC1768 interfaces with the AD5933 via the I2C bus to display readings on an LCD and store data in a database. Bold et al. [14] proposed a wide-band antenna for non-invasive blood glucose monitoring. The study emphasizes using electromagnetic waves, leveraging the correlation between blood glucose levels and changes in permittivity and conductivity, which affect the antenna's resonant frequency. The proposed broadband antenna operates between 500 MHz and 6 GHz, achieving a return loss as low as -33 dB and less than -10 dB across the spectrum. It demonstrates a radiation pattern with a gain of 2.21 dB at the 1.6 GHz resonance frequency. Thati et al. [15] introduced a non-invasive blood glucose screening method based on breath acetone analysis. The study presents a novel approach that estimates blood glucose concentration by quantifying acetone levels in exhaled breath using a semiconductor metal oxide sensor. A correlation between blood glucose levels and exhaled acetone was established. Environmental factors such as temperature, pressure, and humidity were also considered. Feature extraction was performed using waveform data from the sensor, and an artificial neural network (ANN) was trained and evaluated with patient data ranging from 80 mg/dL to 180 mg/dL. The method achieved a glucose estimation error within ± 7.5 mg/dL.

Gayathri et al. [16] investigated a non-invasive blood glucose monitoring approach leveraging near-infrared (NIR) spectroscopy in conjunction with photoplethysmography (PPG). Their system employed linear and polynomial regression models to estimate glucose concentration based on the scattering characteristics of glucose molecules. An MSP430G2553 microcontroller handled the signal processing, and MATLAB was used for data analysis to establish a correlation between photoplethysmographic signals and glucose levels. In a complementary study, Manurung et al. [17] proposed an Internet of Things (IoT)-enabled non-invasive glucose monitoring system based on NIR spectroscopy. Their work integrated a sensor setup comprising an LED-photodiode pair operating at 940 nm, with signal preprocessing conducted via amplification and filtering. Notably, their approach utilized a mobile application embedded with a sequential neural network model developed in Keras and TensorFlow Lite, achieving a mean absolute error of 5.855 mg/dL. The system also featured cloud-based data storage through Firestore, enabling real-time health tracking. Ali et al. [18] introduced a non-invasive blood glucose monitoring (BGM) technique utilizing visible red laser light's transmittance and refractive properties at 650 nm. Unlike conventional near-infrared (NIR)-based systems, their RL-BGM device demonstrated superior tissue penetration, higher sensitivity to glucose-induced refractive index changes, and a faster response time of 7–10 s. The system was validated through in-vitro and in-vivo experiments, including testing on 45 human subjects. Results indicated a linear measurement range up to 450 mg/dL with an overall accuracy of 90–92%, as confirmed via Clarke Error Grid (CEG) analysis. The low-cost, compact hardware design, with minimal electronic components, underscores its potential for practical deployment in point-of-care applications. More recently, Sharma et al. [19] proposed a highly sensitive, non-invasive biosensing platform for glucose detection in saliva using solid-state thin-film transistors (TFTs). The device, fabricated using a tri-channel In_2O_3/ZnO heterojunction, incorporates surface-immobilized glucose oxidase to enable selective glucose detection via changes in charge density at the transistor channel. The sensor demonstrated a wide detection range from 500 nM to 20 mM and achieved an exceptionally low detection limit of 365 pM in artificial saliva and 416 nM in real saliva, with response times under 60 seconds. The BioTFTs exhibited good operational stability and specificity, making them suitable for rapid, point-of-care diagnostic applications.

The reviewed literature demonstrates various non-invasive glucose monitoring techniques, including bio-impedance sensing, electromagnetic coupling, laser and NIR-based spectroscopy, and biochemical sensing through saliva and breath acetone. Many of these approaches incorporate advanced signal processing and machine learning algorithms, with several studies leveraging IoT integration for real-time tracking and remote accessibility. While each method presents unique advantages, challenges such as complexity, selectivity, calibration needs and user comfort persist. The present work builds upon these efforts by integrating breath acetone detection—a proven, pain-free biomarker approach—with IoT-enabled data transmission. This alignment addresses current limitations and enhances usability, real-time responsiveness, and remote monitoring capabilities in diabetes management.

3. Methodology

The proposed non-invasive glucose monitoring system utilizes three sensors to detect five key parameters that aid in estimating breath acetone levels: barometric pressure using the BMP180 sensor, temperature and humidity using the DHT11 sensor, and acetone concentration through the Figaro TGS822 sensor. These sensors are integrated with an Arduino Uno R3 microcontroller and housed within a closed breath analysis chamber to ensure consistent environmental measurements.

The BMP180 and DHT11 sensors are crucial in estimating breath volume and flow rate, which can vary significantly between individuals. Given that exhaled breath is inherently warm and humid, it is essential to compensate for the effects of temperature, humidity, and pressure when interpreting acetone sensor readings. Environmental conditions significantly influence the sensitivity of the gas sensor (TGS822); thus, these parameters are measured and incorporated into the analysis for each individual. Figure 1 illustrates the overall block diagram of the glucose detection system.

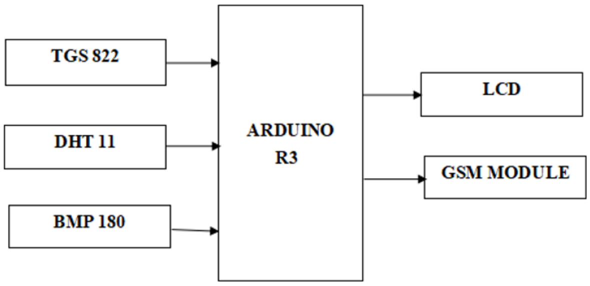

Figure 1: Block diagram of the proposed non-invasive glucose monitoring system

The DHT11 sensor operates at 5V DC and transmits 40 bits of data to the microcontroller: 16 bits for relative humidity (8 integer and 8 decimal), 16 bits for temperature (8 integer and 8 decimal), and an 8-bit checksum. The Arduino Uno processes this data to obtain real-time temperature and humidity readings used in sensor calibration and environmental compensation.

3.1. Measurement of the glucose level

As shown in Figure 2, the hardware setup includes the Arduino Uno R3 connected to the DHT11, BMP180, and TGS822 sensors. Each sensor is tested under ambient air conditions, and output values are recorded and processed using Arduino-based firmware.

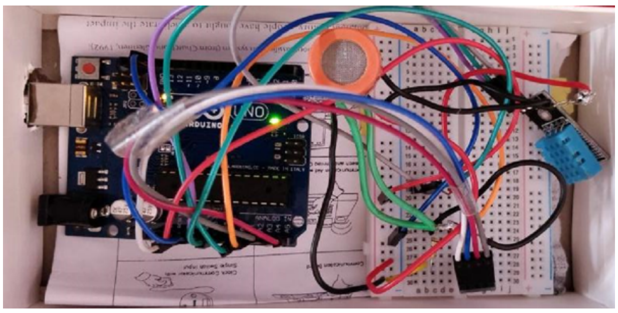

Figure 2: Hardware implementation of the glucose monitoring prototype

3.2. Sensor calibration

The TGS822 gas sensor is calibrated using a standard gas concentration of 300 ppm ethanol. The baseline resistance R_0 at this concentration is calculated using the equation (1):

$$R_S = \left(\frac{V_C - V_{RL}}{V_{RL}} \right) \cdot R_L \tag{1}$$

Here, R_S is the sensor resistance in a target gas, V_C is the circuit voltage, V_{RL} is the load voltage, and R_L is the load resistance. Once R_0 is established, the sensor response is measured for different concentrations, and the corresponding R_S values are used for further analysis.

3.3. Regression analysis

The TGS822 sensor responds to the presence of acetone by decreasing its resistance. This change is influenced by environmental parameters such as temperature, humidity, and gas concentration. The acetone concentration in parts per million (ppm) can be calculated using power regression, given by equation (2):

$$\text{ppm} = \left(a \cdot \frac{R_S}{R_0} \right)^b \tag{2}$$

where a and b are empirically derived constants based on the sensor's characteristic curve. The final glucose concentration in mg/dL is computed by mapping the acetone ppm values through linear regression models. This result is displayed in real-time on a Liquid Crystal Display (LCD) attached to the system. IoT integration (via GSM or Wi-Fi module) allows for optional cloud-based storage and remote patient data monitoring.

4. Results and Discussion

4.1. Environmental Conditions Monitoring

Figure 3 and Figure 4 show sample outputs from the DHT11 and BMP180 sensors during breath input. The DHT11 consistently recorded a temperature of 28–34°C and relative humidity of 68–87%, while the BMP180 recorded atmospheric pressure around 100860–100865 Pa. These parameters compensated for environmental variations affecting the TGS822 gas sensor.

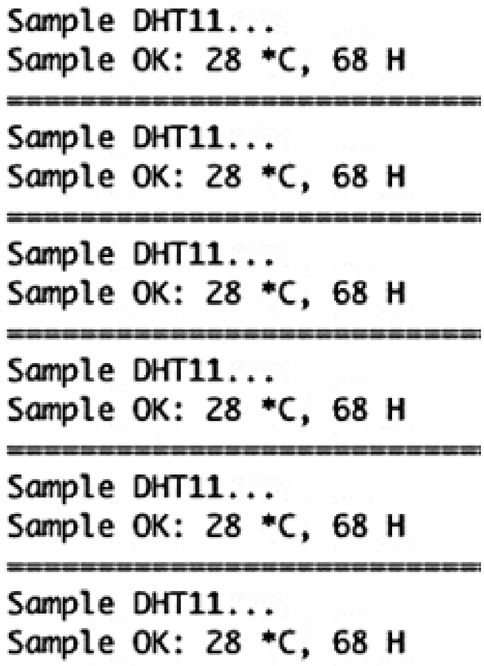

Figure 3: DHT11 sensor output showing temperature and humidity readings

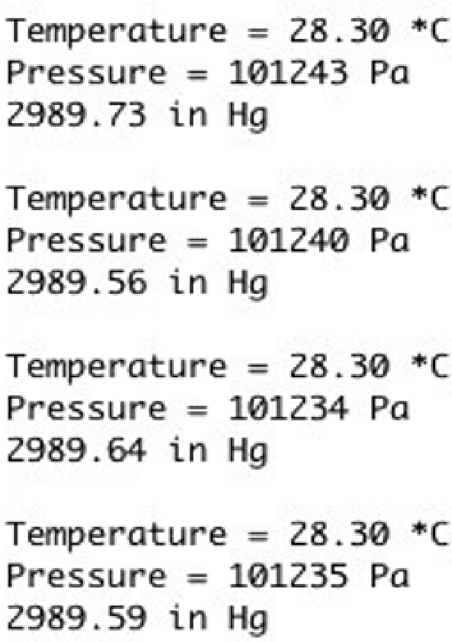

Figure 4: BMP180 sensor output displaying temperature and pressure

4.2. Voltage and Resistance-Based Gas Discrimination

Sensor responses to acetone, ethanol, and benzene were studied across a concentration range of 1–7 ppm. Tables 1 and 2 provide the corresponding voltage and resistance values. Acetone consistently produced the lowest voltage and resistance for a given concentration, indicating higher sensitivity of the TGS822 sensor to acetone.

Table 1: Sensor output voltage (V) at varying gas concentrations

Concentration (ppm)	Acetone	Ethanol	Benzene
1	0.09	0.16	0.27
2	0.10	0.18	0.28
3	0.11	0.20	0.29
4	0.12	0.21	0.30
5	0.13	0.22	0.33
6	0.14	0.24	0.34
7	0.145	0.25	0.36

Table 2: Sensor resistance (Ω) at varying gas concentrations

Concentration (ppm)	Acetone	Ethanol	Benzene
1	5713.10	6623.21	7845.44
2	5002.04	6180.11	7221.76
3	4661.90	5247.43	6454.65
4	4066.67	5111.98	6012.32
5	3651.40	4780.31	5538.55
6	3118.54	4065.89	5278.12
7	2832.33	3799.90	4283.33

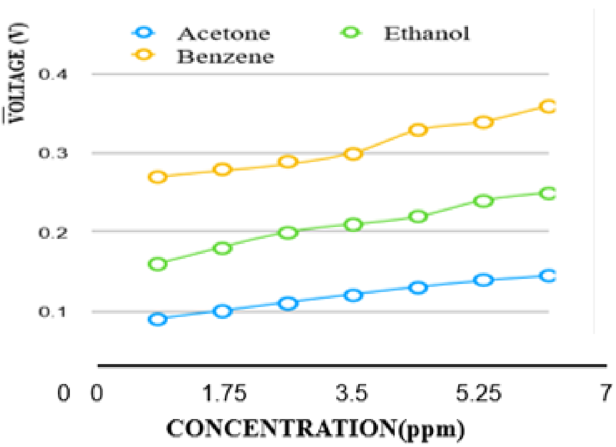

Figure 5: Voltage vs. concentration for different gases

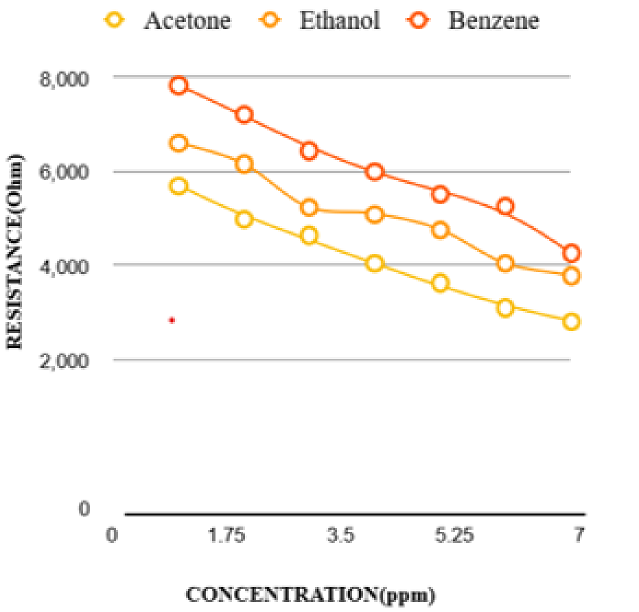

Figure 6: Resistance vs. concentration for different gases

From the figures 5 and 6, it is seen that acetone shows a stronger sensor response at lower concentrations than other gases, confirming that the TGS822 sensor is most suitable for breath acetone detection in this context.

4.3. Real-Time Breath Analysis Output

Real-time outputs from the system show breath acetone levels and the corresponding estimated blood glucose levels (BGL). The processed results are displayed on an LCD. Fig. 7–9 illustrate the readings for non-diabetic and diabetic individuals, respectively.

Figure 7: Breath acetone and estimated BGL for a non-diabetic individual

Figure 8: System vs. Accu-Chek reading for normal BGL

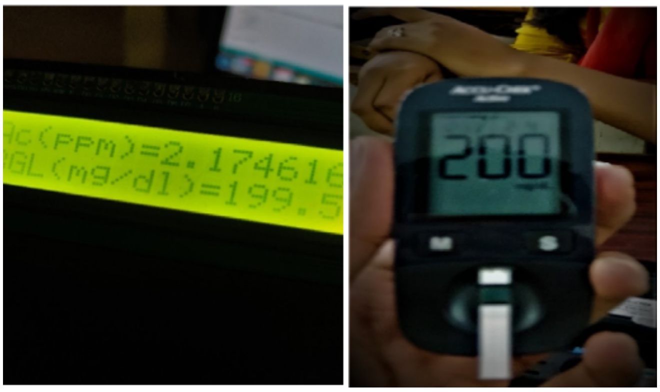

Figure 9: System vs. Accu-Chek reading for elevated BGL

4.4. Volunteer Data and Validation

The system was tested on 11 volunteers, including both diabetic (D1–D4) and non-diabetic (N1–N6) individuals. Table 3 presents the recorded breath acetone levels, system-predicted blood glucose levels, and reference values from Accu-Chek.

Table 3: Comparison of breath acetone and BGL with Accu-Chek values

Volunteer	Acetone (ppm)	BGL (mg/dL)	Accu-Chek (mg/dL)
D1	1.73	164.66	165
D2	1.42	138.35	137
D3	1.19	117.87	116
D4	2.18	199.5	200
D4	1.02	110.73	110
N1	0.96	103.12	104
N2	0.90	100.47	101
N3	0.88	96.4	95
N4	0.86	92.16	91
N5	0.85	87.34	88
N6	0.80	84.33	83

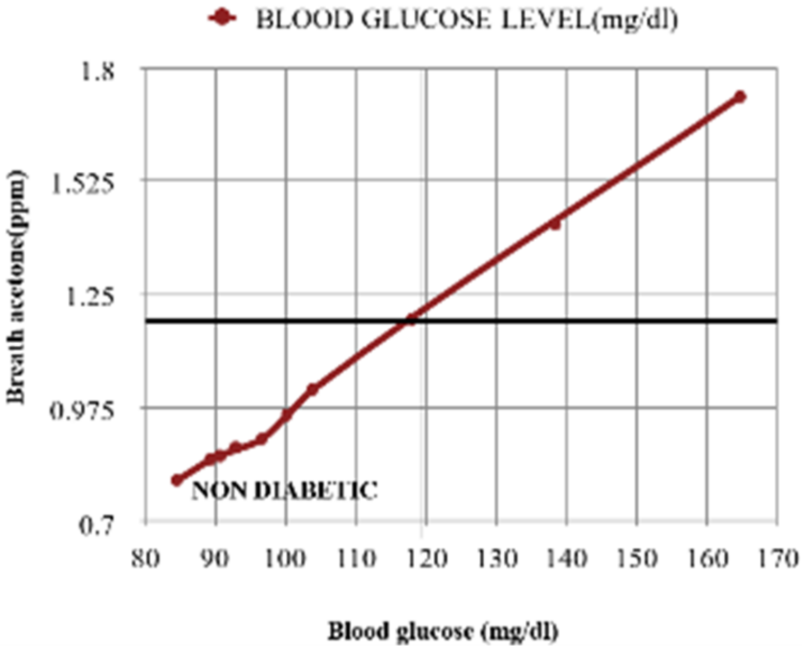

Figure 10: correlation between breath acetone and blood glucose levels

As illustrated in Fig. 10, a clear positive correlation is observed between breath acetone concentration and blood glucose levels. For healthy individuals, breath acetone levels remain below 1.20 ppm, corresponding to BGL values within the normal range (80–110 mg/dL). Diabetic individuals exhibit higher acetone values exceeding 1.2 ppm, corresponding to elevated glucose levels above 120 mg/dL. The system achieved an average accuracy of approximately 98%, with an error range of 1.6–2% when compared against standard glucometer readings. These results confirm the potential of the proposed non-invasive, breath-based system as a reliable alternative for routine glucose monitoring.

5. Conclusions

This study presents a non-invasive, IoT-integrated glucose monitoring system using a Figaro TGS822 gas sensor based on breath acetone detection. The system also incorporates DHT11 and BMP180 sensors for environmental parameters such as temperature, humidity, and pressure, influencing gas sensor behavior. A correlation between breath acetone concentration and blood glucose level was established through regression analysis. The prototype displays glucose levels in real-time and transmits data for remote monitoring. Experimental results from 11 volunteers, including diabetic and non-diabetic subjects, confirmed the system's accuracy when validated against standard glucometer readings. The system achieved an accuracy rate of approximately 98%, with only minor deviations. These findings validate the feasibility and reliability of breath-based glucose monitoring as a non-invasive, low-cost alternative for diabetes management. Future work may explore miniaturization, integration with mobile apps, and long-term clinical validation to enable widespread adoption in personalized healthcare.

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contributions

V. Mythily: Conceptualization, Supervision, Review and Editing; **Bhuvaneshwari GT**: Methodology, Investigation, Writing – Original Draft, Data Curation; **Madumitha S**: Software, Validation, Visualization; **Divyashree S**: Hardware Implementation, Testing, Formal Analysis.

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