

A Non-Invasive Glucose Monitoring Device using Near Infra-Red

P. Vanathi¹, R. Monica^{2*}, J. Prasanthi³, T. Bavani⁴, T. Logasundari⁵, A. Kavnilavu⁶

^{1,2,3,4}B.Tech., Department of Biomedical Engineering, Sri Venkateshwaraa College of Engineering and Technology, Puducherry, India

^{5,6}Assistant Professor, Department of Biomedical Engineering, Sri Venkateshwaraa College of Engineering and Technology, Puducherry, India

Abstract: In a developing country like India, systemic chronic diseases reach unsustainable heights as the population grows. According to WHO, diabetes affects an estimated 28.7 million people worldwide, or 28.5% of the population. Diabetes affects around 8.5 million people who have yet to be diagnosed (2022). Diabetes is one of these metabolic systemic chronic diseases that has captured the world's attention. The primary goal of our research is to develop non-invasive blood glucose monitoring technology that will benefit a large number of patients. We analyze the research progress and significant problems of non-invasive blood glucose detecting technologies in our project evaluation. In our study, we present an effective NIR-based optical detecting system. The existing non-invasive glucose monitoring device had a 60% accuracy level, however the proposed model will have an accuracy of 80% and will have a significant advantage over the existing system. Furthermore, the information is continuously delivered to the personal computer via serial communication via the UART protocol.

Keywords: Diabetes, non-invasive, bio-impedance, glycemic, continuous glucose monitoring, hyperglycemia, hypoglycemia.

1. Introduction

Controlling blood glucose levels diligently and on time has recently emerged as a critical component in diabetes treatment [1]. Diabetes can cause kidney failure, limb amputation, heart attacks, strokes, and even death. A non-invasive approach for determining glucose content either directly measures an inherent molecular feature of glucose or the influence of glucose on the optical properties of tissues or blood [2]. Type 1 diabetes patients should check their blood glucose levels four times a day, whereas type 2 patients should check twice a day, as advised by the diabetic association. Within 1-2 hours after a meal, this diabetes ranges from 0.72 to 1.4 mg/ml [3].

The American Diabetes Association's target range of 110-140 mg/dl (6.11-10.0 mmol/liter) for critically ill patients and the American Association of Clinical Endocrinologists' recommendation of 110 mg/dl (6.11 mmol/liter) as the upper cutoff concentration for glucose in critically ill patients [4] are based on growing evidence for the value of tight glycemic control in the management of diabetic patients. A cross-sectional study correlating current retrospective 3-day time in target range with varying degrees of diabetes retinopathy, as well as an analysis of the 7-point self-monitored blood glucose

data from the diabetes control and complication trial, show a correlation of time in target range (70-180 mg/dl [3.9-10.0 mmol/L]) with diabetes complication. There is apparently a link between time spent in the target range and the number of severe and non-severe hypoglycemia incidents. Each subgroup's recommendations were presented to the whole panel and voted on [5].

NIR spectroscopy is frequently utilized for analysis and quality control in the food and pharmaceutical industries. There are numerous approaches for classifying samples based on spectroscopic data. Frequently, the classification technique chosen depends first on the data structure under consideration and is led by the prediction performance obtained with this model [6]. According to the International Diabetes Federation, diabetes caused 5 million deaths and a \$1197 billion health-care expenditure worldwide in 2015, and by 2040, there would be approximately 642 million diabetic people worldwide. Despite the rising prevalence, there is a lack of vaccine and treatment to prevent this condition, therefore frequent blood glucose testing and monitoring have become an essential aspect of diabetes care management. The current method of measurement is invasive, requiring the use of a commercial glucometer. A blood sample must be obtained and examined using a glucometer instrument, either from a vein or by pricking the fingertip. This procedure is uncomfortable and causes agony for patients, especially those who must repeat it several times per day to maintain adequate metabolic body control [7]. To begin, the polygraph system measures the bioimpedance of a forearm at each cardiac cycle at a sample rate of 1000 Hz. The difference between the minimum and maximum bioimpedance readings at each cardiac cycle is then calculated. Second, the bioimpedance fluctuation caused by changes in blood glucose concentration will be studied. We propose to use bioimpedance subtraction to dissociate the influence of blood volume pulsation and other tissues (skin, fat, muscle, and so on) on glucose readings [8].

2. Related Work

Diabetes is a serious public health problem that affects over 451 million people worldwide. Physiological and experimental characteristics impact the accuracy of non-invasive glucose monitoring, which must be addressed before replacing the

*Corresponding author: monicadinesh086@gmail.com

finger prick method. Furthermore, using machine learning techniques correctly may significantly improve the accuracy of glucose estimates. One objective of this study is to use light sources with varied wavelengths to increase the sensitivity and selectivity of glucose detection in an aqueous solution. Multiple-wavelength measurements allow for the correction of errors caused by differences in blood and tissue components between and within people. This paper investigates the transmission measurements of a custom-built optical sensor using 18 different wavelengths spanning from 410 to 940 nm. The findings demonstrate a substantial connection (0.98) between glucose content and transmission intensity at four wavelengths (485, 645, 860, 940 nm). Five machine learning techniques are being investigated for glucose prediction. When regression approaches are used, 9% of glucose predictions (normal, hypoglycemic, or hyperglycemic) are inaccurate. The use of classification techniques to data sets separated into 21 groups improves prediction accuracy. The data from each class corresponds to a different 10 mg/dL glucose range. Classification-based models outperform regression, and the support vector machine is the most effective, with an F1-score of 99%. In addition, the Clarke error grid shows that 99.75% of glucose readings are within clinically acceptable ranges. This is an essential step toward a critical diagnosis in an emergency patient situation [3].

Noninvasive blood glucose monitoring (NBGM) is a potential alternative for diabetic patients, offering the benefits of painless and continuous monitoring. The conductivity and relative permittivity of aqueous solutions with varied glucose concentrations were measured using an impedance analyzer in the frequency range of 1 kHz to 1 MHz to better describe the response of glucose to radio-frequency (RF) signals at low frequencies. In addition, taking into account blood volume pulsation during the cardiac cycle, a new technique for NBGM based on measuring bioimpedance was given in this study. To validate the aforementioned technique, an inhomogeneous arm model with three tissue layers (blood, blood vessels, and other necessary tissues) was developed. Furthermore, the measurements were made using *in vitro* and *in vivo* tests, respectively. When the frequency of the RF signal was less than 1 MHz, the findings revealed that as the glucose content grew, the conductivity of aqueous solutions decreased. The relative permittivity, on the other hand, was practically indifferent to glucose content. The arm model simulation result revealed that when glucose concentration increased, the bioimpedance difference of blood volume reduced. Both *in vitro* and *in vivo* investigations corroborated this. As a result, we believe that the suggested technique for NBGM has practical applicability [5].

The Mueller optical coherence tomography technology and a genetic algorithm are used to extract two optical characteristics, namely the optical rotation angle and the depolarization index, to determine the glucose content on the human fingertip. The practicality of the suggested approach is proved by measuring the optical rotation angle and depolarization index of low and high scattering aqueous glucose solutions, respectively. The optical rotation angle and depolarization index for both solutions are demonstrated to change almost linearly with

glucose content. As a consequence, the suggested method's capacity to determine glucose levels using just two optical characteristics is proven. The suggested technique's practical applicability is proved by measuring the optical rotation angle and depolarization index on the human fingertip of healthy volunteers under different glucose levels [1].

In a number of healthcare settings, glucose meters are generally utilized in the therapy of hypoglycemia and hyperglycemic illnesses. However, determining the accuracy of glucose meters is difficult. Glucose meters can only assess whole blood, and glucose in whole blood is unstable. The degree of agreement between a test result and the real value of an analyze is defined as technical accuracy. Isotope dilution mass spectrometry is used to determine the truth for glucose, and frozen serum standards evaluated in this manner are available from the National Institute of Standards and Technology. The truth about entire blood is unknown, and cells must be isolated from the total blood matrix before being analyzed using isotope dilution mass spectrometry. Glucose meters cannot examine serum, and isotope dilution mass spectrometry is not widely accessible in most hospitals and diabetes clinics to check glucose meter accuracy. According to consensus guidelines, whole blood analysis on a glucose meter should be compared to plasma or serum centrifuged from a capillary sample and examined by a clinical laboratory comparison technique. When the differences between venous and capillary blood are examined, capillary samples may not give enough volume to test by both techniques, and venous samples may be utilized as an alternative. As a result, establishing technical correctness is complicated, and there is no clear agreement among standards organizations and professional societies on accuracy requirements. Clinicians, on the other hand, are more interested with the glucose meter's clinical concordance with a serum or plasma laboratory result [6].

We present a methodological technique based on a grid search to guide the selection of SVM parameters in order to decrease classification error rate while also depending on visualization of the number of support vectors (SVs). We also show an interest in displaying the SVs in main component subspaces to have a better understanding of the trained SVM's interpretation. The suggested approaches are tested on two NIR datasets: a somewhat nonlinear 2-class issue and a more difficult 3-class challenge. The improved SVM models are fairly sparse, depending on 8 and 35 support vectors, respectively, and achieve high classification scores (98.9% and 91% on the test sets, respectively) [10].

Noninvasive blood glucose monitoring (NBGM) is a potential alternative for diabetic patients, offering the benefits of painless and continuous monitoring. The conductivity and relative permittivity of aqueous solutions with varied glucose concentrations were measured using an impedance analyzer in the frequency range of 1 kHz to 1 MHz to better describe the response of glucose to radio-frequency (RF) signals at low frequencies. In addition, taking into account blood volume pulsation throughout the cardiac cycle, a novel technique for NBGM based on measuring bioimpedance was given in this

study. To verify the aforementioned technique, an inhomogeneous arm model with three tissue layers (blood, blood vessels, and other necessary tissues) was developed. Furthermore, the measurements were made using in vitro and in vivo tests, respectively. When the frequency of the RF signal was less than 1 MHz, the findings revealed that as the glucose content grew, the conductivity of aqueous solutions decreased. The relative permittivity, on the other hand, was practically indifferent to glucose content. The arm model simulation result revealed that when glucose concentration rose, the bioimpedance difference of blood volume reduced. Both in vitro and in vivo investigations corroborated this. As a result, we believe that the suggested technique for NBGM has practical applicability [9].

3. Working Process

The non-invasive blood glucose sensor detects the amount of glucose without inflicting any damage. In Fig. 1, if it surpasses the threshold level, all information on the PC is updated through UART. The AT89S52 comes bundled with the following features: 8K bytes of flash memory, 256 bytes of RAM memory, 32 I/O lines, a watchdog timer, two data pointers, three 16-bit timers and counters, a six-vector two-level interrupt architecture, a full duplex serial port, an on-chip oscillator, and clock circuits are all included. Furthermore, the AT89S52 has static logic allowing operating at zero frequency and two software-selectable power-saving modes. Idle Mode turns off the CPU while leaving the RAM, timers and counters, serial port, and interrupt system running. The power-down mode maintains RAM data but disables all other chip operations until the next interrupt or hardware reset.

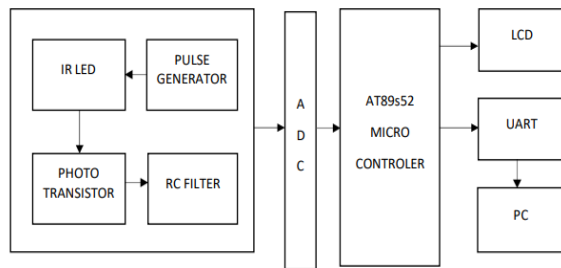


Fig. 1. Block diagram of non-invasive glucose monitoring device

A NIR light source, a PIN photo diode, signal processing, an ADC, a microcontroller unit, and an LCD are shown in the circuit diagram. NIR spectrometry may be used to assess blood glucose levels. This technique is low-cost and simple; however, it suffers from dispersion and has a weak connection with blood glucose levels. The light signal is converted into a voltage signal by the photodiode. The voltage signal has a range of mV. The signal processing device detects blood glucose levels and converts them into electrical signals. An ADC converts an analog signal to a digital signal. The ATMEL microcontroller AT89S52 controls the whole system. The output is shown on an LCD. If it surpasses the threshold level, all information on the PC is updated through UART. The UART controller manages asynchronous serial communication between a

computer and a peripheral device attached to the computer's serial port, converting data from serial to parallel and vice versa. This enables the computer to communicate with modems and other serial devices.

4. Hardware Requirement

The main hardware components used for implementing this device are:

- 1) Microcontroller
- 2) NIR sensor
- 3) ADC
- 4) RS232 cable
- 5) LED display

A. Microcontroller



Fig. 2. AT89S52 Microcontroller

Our system's brain is the microcontroller. It will be in charge of all data processing and transmission. The AT89S52 is a low-power, high-performance CMOS 8-bit microcontroller with 8K bytes of flash memory in-system. The device is built using high-density nonvolatile memory technology from Atmel and is compatible with the industry-standard 80C51 instruction set and connector.

B. NIR Sensor



Fig. 3. NIR sensor

NIR sensing offers information about items in the physical world to machines. When NIR light is produced and reflected off of an item, an NIR sensor detects the reflected light or light pattern and uses it to calculate the distance, size, position, and identifying properties of objects in the three-dimensional environment.

C. ADC



Fig. 4. ADC

An analogue-to-digital converter (ADC) is an electrical circuit that measures a real-world signal (such as temperature, pressure, acceleration, or speed) and transforms it to a digital representation of the signal.

D. RS232 Cable



Fig. 5. RS232 cable

RS232 connections link a DTE (data terminal equipment) like a desktop computer to a DCE (data communications equipment), which is usually a modem, printer, or special-purpose peripheral. It is used to connect the device to the computer through serial communication via UART.

E. LCD Display

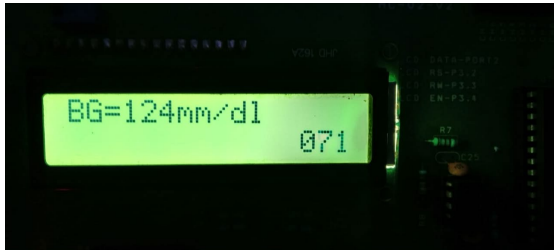


Fig. 6. LCD display

A flat panel display that employs an array of light-emitting diodes as pixels for video display is known as an LCD display. Because of their brightness, they may be utilized for shop signs and billboards outside, where they are visible in the sun. The output is shown on the LCD monitor.

F. Other Components

Other components include connecting wires, the Keil compiler, and the PCB board. The PCB board is used to place the components, and connecting wires are used to connect the components to the PCB board.

5. Result and Discussion

The overview of table 1 for patient’s sugar value and conditions is provided in this section.

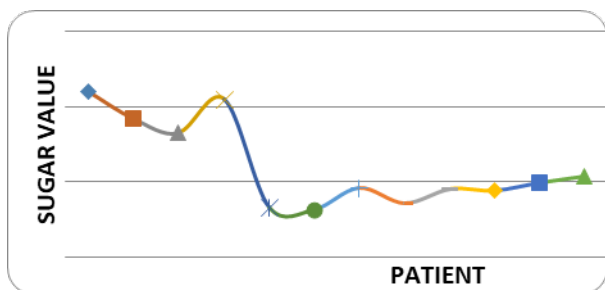


Fig. 7. Graphical representation of glucose level in blood

Table 1
Patients’ glucose level in blood

Patients	Age	Gender	Normal range	Sugar value	Condition
A	25	F	70-110	92	Normal
B	20	F	70-110	72	Normal
C	40	M	70-110	90	Normal
D	37	F	70-110	88	Normal
E	32	M	70-110	99	Normal
F	22	M	70-110	108	Normal
G	57	F	70-110	66	Hypoglycemia
H	54	F	70-110	63	Hypoglycemia
I	60	M	70-110	220	Hyperglycemia
J	47	M	70-110	184	Hyperglycemia
K	62	M	70-110	165	Hyperglycemia
L	48	F	70-110	210	Hyperglycemia

Above mentioned table and graph represent the values of the patient’s glucose level which present in the blood. In this table there are three types of disorder is present first normal (70-110), second Hypoglycemia (below 70) and the last is Hyperglycemia (above 110). The existing non-invasive glucose monitoring device had a 60% accuracy level; however, the proposed model will have an accuracy of 80% and will have a significant advantage over the existing system. Furthermore, the information is continuously delivered to the personal computer via serial communication via the UART protocol.



Fig. 8. Prototype of a noninvasive glucose monitoring device using NIR

6. Conclusion

There are numerous plans in the present sector for future study and development of measuring and monitoring technologies. In vitro studies were used to show glucose monitoring using non-invasive spectroscopic approaches. The non-invasive glucose monitoring technique is inexpensive to manufacture and maintain, and it performs well in in vitro experiments. The verified prototype shows a highly promising future for NIR technology adoption in the biomedical arena, particularly in optical spectroscopy for non-invasive glucose monitoring in real-time and constantly. The NIR spectroscopy experiment shows considerable promise for non-invasive glucose level continuity in the human body. Other conceivable factors not included in this research, such as skin roughness, which may cause light scattering, the content of different bodily

fluids, and so on, may have no effect on system performance. In order to increase system calibration and sensitivity even further, we will evaluate the influence of these factors on sensor system performance in our future research. The present model will be optimized and refined, resulting in a significantly stronger link between system inputs and outputs. As a result, the suggested non-invasive system's performance will be enhanced even more. Future experiments will concentrate on enhancing the device's accuracy and resilience so that real-time glucose measurement and monitoring, as well as data transfer to display devices, may be accomplished. Multivariate regression will be used to strengthen the system for in vitro testing. This would have a significant influence on the monitoring of personal health and the history of diabetic patients.

Acknowledgment

The authors would like to express their sincere thanks to Mrs. T. Logasundari, Assistant Professor, Ms. A. Kavinilavu, Assistant Professor, Ms. M. Sowmiya, Assistant Professor, Mr. A.V. Srinath, Assistant Professor, Department of Biomedical Engineering, and Mr. S. Balaji, Head of Department, Sri Venkateshwaraa College of Engineering and Technology, Puducherry for their helpful support, constant encouragement, and contributions to the project.

References

- [1] J. L. Parkes, S. L. Slatin, S. Pardo, and B. H. Ginsberg, "A new consensus error grid to evaluate the clinical significance of inaccuracies in the measurement of blood glucose," *Diabetes Care*, vol. 23, no. 8, pp. 1143–1148, Aug. 2000.
- [2] T.-L. Chen, Y.-L. Lo, C.-C. Liao, and Q.-H. Phan, "Noninvasive measurement of glucose concentration on human fingertip by optical coherence tomography," *J. Biomed. Opt.*, vol. 23, no. 4, p. 1, Apr. 2018.
- [3] A. E. Omer, S. Gigoyan, G. Shaker, and S. Safavi-Naeini, "WGM-based sensing of characterized glucose-aqueous solutions at mm-waves," *IEEE Access*, vol. 8, pp. 38809–38825, 2020.
- [4] O. Devos, C. Ruckebusch, A. Durand, L. Duponchel, and J.-P. Huvenne, "Support vector machines (SVM) in near infrared (NIR) spectroscopy: Focus on parameters optimization and model interpretation," *Chemo-metric Intell. Lab. Syst.*, vol. 96, no. 1, pp. 27–33, Mar. 2009.
- [5] J. Li, T. Igbe, Y. Liu, Z. Nie, W. Qin, L. Wang, and Y. Hao, "An approach for noninvasive blood glucose monitoring based on bioimpedance difference considering blood volume pulsation," *IEE Access*, vol. 6, pp. 51119–51129, 2018.
- [6] J. Yadav, A. Rani, V. Singh, and B. M. Murari, "Investigations on multisensor-based noninvasive blood glucose measurement system," *J. Med. Devices*, vol. 11, no. 3, Sep. 2017.
- [7] X. Xiao, Q. Yu, Q. Li, H. Song, and T. Kikkawa, "Precise noninvasive estimation of glucose using UWB microwave with improved neural networks and hybrid optimization," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–10, 2021.
- [8] Hu, S. Nagae, and A. Hirose, "Millimeter-wave adaptive glucose concentration estimation with complex-valued neural networks," *IEEE Trans. Biomed. Eng.*, vol. 66, no. 7, pp. 2065–2071, Jul. 2019.
- [9] M. Islam, M. S. Ali, N. J. Shoumy, S. Khatun, M. S. A. Karim, and B. S. Bari, "Non-invasive blood glucose concentration level estimation accuracy using ultra-wide band and artificial intelligence," *Social Netw. Appl. Sci.*, vol. 2, no. 2, p. 278, Feb. 2020.
- [10] R. J. Casson and L. D. Farmer, "Understanding and checking the assumptions of linear regression: A primer for medical researchers: Assumptions of linear regression," *Clin. Experim. Ophthalmol.*, vol. 42, no. 6, pp. 590–596, Aug. 2014.