iGLU: An Intelligent Device for Accurate NonInvasive Blood Glucose-Level Monitoring in Smart Healthcare

Prateek Jain
Malaviya National Institute of Technology

Amit M. Joshi
Malaviya National Institute of Technology

Saraju P. Mohanty
University of North Texas

***Abstract*—In case of diabetes, fingertip pricking for blood sample is inconvenient for glucose measurement. Invasive approaches like laboratory test and one touch glucometer enhance the risk of blood related infections. To mitigate this important issue, in the current paper, we propose a novel Internet-of-Medical-Things (IoMT) enabled edge-device for precise, non-invasive blood glucose measurement. The novel device called "Intelligent Glucose Meter" (i.e. iGLU) is based on near-infrared (NIR) spectroscopy and machine learning (ML) model of high accuracy. iGLU has been validated in a hospital and blood glucose values are stored IoMT platform for remote monitoring by endocrinologist.**

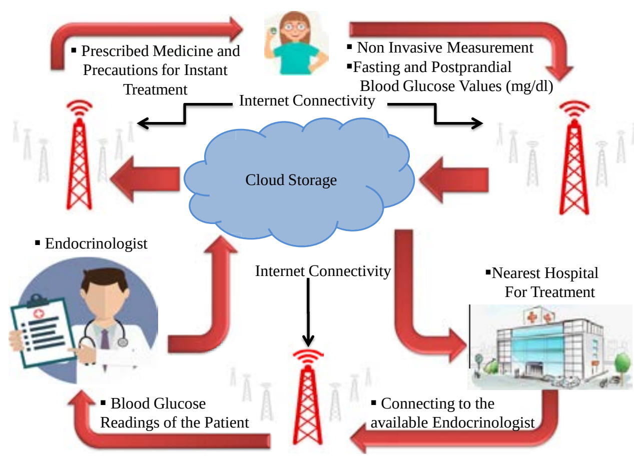


Fig. 1: Blood glucose diagnosis in smart healthcare.

I. Introduction

Smart healthcare system comprises of ambient intelligence, quality of service and also offers continuous support of the critical diseases monitoring [1], [2]. This system is most demandable for remote monitoring of diabetic patients with low cost and rapid diagnosis [3]. Traditional blood glucose measurement is unable to serve everyone's need at remote location. Despite having good diagnostic centers for clinical test facility in urban area, medical services are not approachable to everyone at remote location [4], [5]. It is necessary to monitor blood glucose of diabetic patients where diagnosis facility are not easily available. The instant diagnose of blood glucose and frequent monitoring are the recent challenges in smart healthcare. The process flow of blood glucose diagnosis in smart healthcare is depicted in Figure 1.

IoMT enabled handheld non-invasive glucose measurement end-device has strong potential for rapid monitoring as well as to facilitate the interact with endocrinologist to the remote located diabetic patients where diagnosis centers and hospitals are not easily available. According to this environment, patients measure their glucose without pricking blood and directly store to the cloud where nearby endocrinologist can monitor the glucose data of each patient. The prescription would also be provided by endocrinologist to the remote located patient for further treatment. The ubiquity of diabetic patients has become double from 2010 over the world. The estimated diabetes dissemination from 2009 is 290 million and is expected to affect 450 million people by 2030. Hence, it is essential to develop the glucose measurement device for rapid diagnosis of diabetes. People will be more conscious for their glucose level with frequent monitoring. Invasive method for glucose measurement is not advisable in case of continuous monitoring. Therefore, it required to design the non-invasive device for clinical tests, which is beneficial for health care. In proposed work, optical detection is involved. Blood glucose is predicted by machine learning based computation model.

II. State-of-Art in Blood Glucose-Level Measurement

Blood glucose measurement is possible using invasive, minimally invasive and non-invasive methods (Figure 2). Frequent pricking, as needed in invasive methods, for glucose measurement causes trauma. Therefore, the semi-invasive approach has the advantage of continuous glucose monitoring without multiple times pricking. However, non-invasive methods can completely eliminate pricking which opens door to painless and continuous glucose monitoring (CGM).

A. Invasive Methods

A low-invasive amperometric glucose monitoring biosensor has been proposed using fine pointed glucose oxidase immobilized electrode which doesn't require more than 1mm in length to be inserted in skin [6]. A fully implanted first-generation prototype sensor has been presented for long-term monitoring of subcutaneous tissue glucose [7]. This wearable sensor which is integrated as an implant is based on a membrane containing immobilized glucose oxidase and catalase coupled to oxygen electrodes, and a telemetry system.

B. Minimally Invasive Methods

Implantable biosensors have been deployed for continuous glucose monitoring [8]. Wearable minimally invasive microsystem has been explored for glucose monitoring [9]. A microsystem has been presented for glucose monitoring which consists of microfabricated biosensor flip-chip bonded to a transponder chip [10]. A method has been discussed to reduce the frequency of calibration of minimally invasive Dexcom sensor [11]. An artificial pancreas has been represented along with glucose sensor to control diabetes [12]. But, approaches based semi-invasive devices have not been tried for real time application. These wearable microsystems are neither painless nor cost effective solutions.

C. Non-invasive Methods

To make the painless system, photoacoustic spectroscopy has been introduced for non-invasive glucose measurement [13]. However, utilization of LASER makes the setup costly and bulky. An enzyme sensor has been explored for glucose measurement in saliva [14]. Glucose detection is possible using Intensity Modulated Photocurrent Spectroscopy (IMPS) spectroscopy that connects the electrodes to the skin which is affected by sweat [15]. High precision level is not possible through these methods as sweat and saliva properties vary for individuals. The blood glucose measurement has also been explored using Raman spectroscopy in laboratory [16]. The experimental setup for Raman spectroscopy required a large area and will not be portable. Glucose measurement has also been done from anterior chamber of the eye which limits it's usage of continuous monitoring [17]. Blood glucose can been estimated using photoplethysmography (PPG) signal [18], [19].

PPG signal analysis is not based on principle of glucose molecule detection. Therefore, specific wavelengths are not required for glucose estimation. Hence, iGLU is more precise compared to PPG signal analysis based system for glucose measurement. In this way, long NIR wave for optical detection has been considered for glucose measurement which is not comparatively precise glucose measurement system as long wave has shallow penetration [20]. Therefore, small NIR wave is preferred for glucose detection (Figure 3).

Prior works related to glucose monitoring have been discussed which represent wearable and non-wearable approaches. Raman spectroscopy, photoacoustic spectroscopy and invasive approach based systems are not wearable. Minimally invasive devices which have been discussed, are implantable. Other approaches based non-invasive device are wearable. Here, iGLU is non-invasive, optical detection based wearable device for continuous glucose monitoring with IoMT framework.

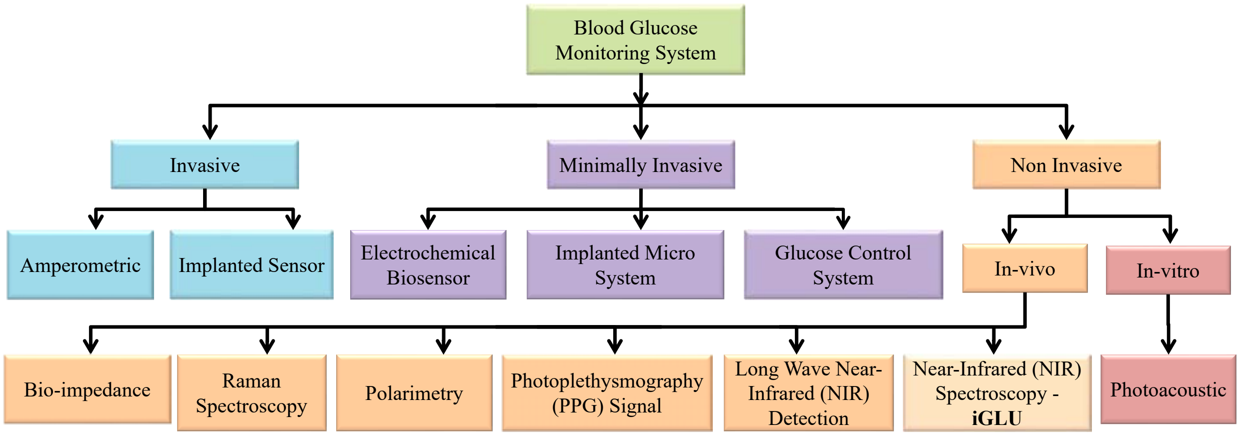


Fig. 2: An overview of various blood glucose-level measurement devices or systems.

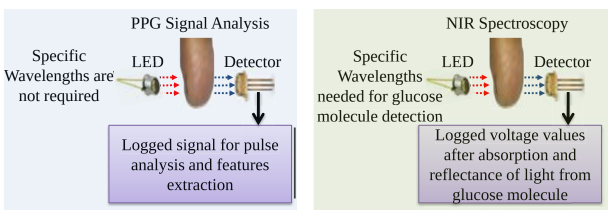


Fig. 3: PPG signal versus NIRS based glucose estimation

D. Consumer Electronics for Glucose-Level Monitoring

Several devices have been developed for non-invasive blood glucose measurement. Some products such as glucotrack, glutrac, glucowise, DiaMon Tech and device from CNOGA medical are not commercialized. Glutrac is multi-parameter health test device with smart healthcare. However, they have limitations in terms of precise measurement. The cost of product is also high which varies in the range of 300-400 USD. Therefore, the cost effective solution for non-invasive blood glucose measurement is needed.

III. Novel Device iGLU to Advance the State-of-Art in Wearable for Continuous Blood Glucose Monitoring

Non-invasive measurement reduces the possibility of blood-related diseases. However, this approach have some limitations such as large set-up, measuring object (ratina) and skin properties (including dielectric constant and sweat level). Therefore, portable non-invasive precise glucose measurement device for continuous monitoring is needed. An initial example is a non-invasive glucose measurement using NIR spectroscopy and Huber's regression model [21]. There are several glucose monitoring systems which neither provide precise measurement nor cost effective solution. These systems are not enabled for smart healthcare. The following questions are resolved in iGLU for the advancement of smart healthcare: (1) How can we have a device that automatically performs all the tasks of blood-glucose monitoring at the user end without internet connectivity and stores the data in cloud for future use by the patient and healthcare providers? (2) Can we have a device that can perform automatically to avoid hassle and risky finger pricking all the time monitoring is needed?

This article introduces an edge-device called "Intelligent Glucose Meter" (i.e. iGLU) for noninvasive, precise, painless, low-cost continuous glucose monitoring at the user-end and stores the data on cloud in an IoMT framework. A non-invasive device has been proposed with precise and low cost solution. The proposed device is also integrated with IoMT where the data is accessible to caretaker for point of care. The device will be portable after packaging to use everywhere. The device is fast operated and easy to use for smart healthcare. The flow of proposed iGLU is represented in Figure 4.

The contributions this article to advance the state-of-art in smart healthcare include the following:

1) A novel accurate non-invasive glucometer (iGLU) by judiciously using short NIR waves

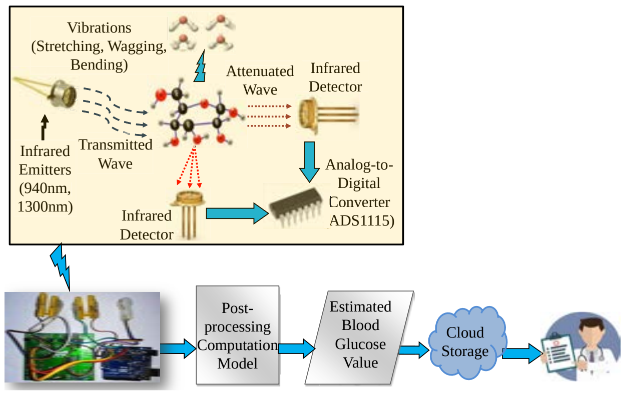


Fig. 4: A conceptual overview of iGLU.

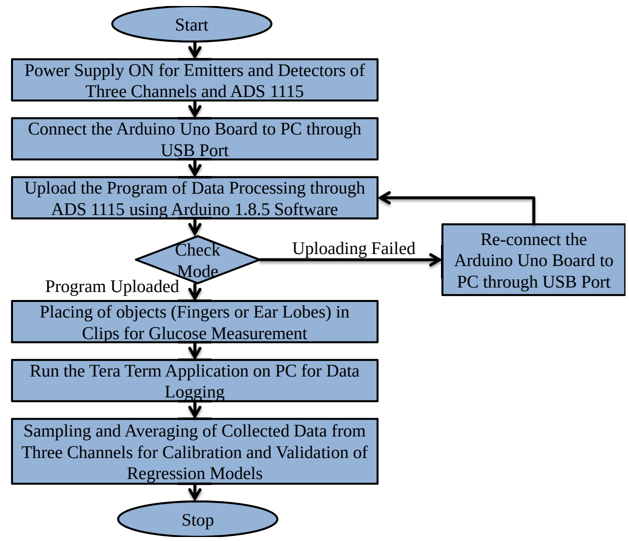


Fig. 5: Process flow data acquisition for iGLU.

with absorption and reflectance of light using specific wavelengths (940 and 1300 nm) has been introduced. The wavelengths are judiciously selected after experimental analysis which has been done in material research center MNIT, Jaipur (India).

2) A novel accurate machine learning based method for glucose sensor calibration has been presented with calibrated and validated healthy, prediabetic and diabetic samples.
3) The proposed non-invasive blood glucose measurement device has been integrated in IoMT framework for data (blood glucose values) storage, patient monitoring and treatment on proper time with cloud access by both the patient and doctor.

IV. Proposed Non-invasive Blood Glucose Measurement Device (iGLU)

The proposed device based on NIR spectroscopy with two short wavelengths is designed and implemented using three channels. Each channel is embedded with emitter and detector of specific wavelength for optical detection. The data is collected and serially processed by 16 bit ADC with sampling rate of 128 samples per second. The logged data is calibrated and validated thorough existing regression techniques to analyse the optimized model. The flow of data acquisition for proposed iGLU is presented in Figure 5.

A. The Approach for Glucose Molecule Detection

Glucose molecule vibrates according to its atomic structure at specific wavelengths. It is analyzed that absorbance and reflectance are sharper and stronger in short wave NIR region [22]. The absorption peak of glucose spectra at 1314 nm has been analyzed [23]. The non-invasive blood glucose measurement using 850, 950 and 1300 nm has been implemented [15]. The 940 nm wavelength for detection of glucose molecule has been identified [24]. NIR spectra of sucrose, glucose and fructose are elaborated with CH_2, CH and OH stretching at 930, 960 and 984 nm, respectively [25].

B. Proposed Module for Data Acquisition

Proposed iGLU uses NIR spectroscopy to improve the accuracy. A 2-Layer PCB has been developed to embed infra-red emitters (MTE1300W -for 1300 nm, TSAL6200 -for 940 nm, TCRT1000 -for 940 nm) and detectors (MTPD1364D -for 1300 nm, 3004MID -for 940 nm, TCRT1000 -for 940 nm). The hardware is designed for data acquisition from emitters, detectors and ADC with 5V DC supply. According to the emitters and detectors, compatible passive components have been chosen. Architecture of glucose sensing is shown in Figure 6. Detectors with daylight blocking filters are packaged and not affected by sweat. ADS 1115 with 860 SPS, 16 bit, I^2C compatible and single ended is controlled through microcontroller ATmega328P and used to convert the data (in Volts) from all channel in decimal form. The noise power and signal-to-noise ratio (SNR) have also been found 0.08 and 25.2 dB, respectively, which show the minimum noise level.

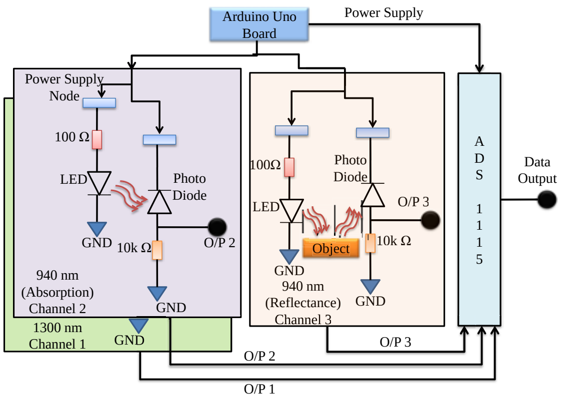


Fig. 6: Circuit topology of proposed device (iGLU).

C. A Specific Prototype of the iGLU

Absorption and reflectance at 940 nm and absorption at 1300 nm are implemented for detection of the glucose molecules. The detector's voltage depends on received light intensity. After placing the fingertip between emitter and detector, the voltage values are logged. Change in light intensity depends upon glucose molecule concentration. During experiments, blood glucose is measured through the invasive device standard diagnostics (SD) check glucometer for validation of the non-invasive results. The reading is taken as referenced blood glucose values (mg/dl). During the process, optical responses through detectors have been collected from 3 channels simultaneously. During measurement, the channels data is collected in the form of voltages from 3 detectors. These collected voltages correspond to referenced blood glucose concentration. These voltage values are converted into decimal form using 4-channel ADS 1115 (Texas Instruments) ADC [26]. Coherent averaging has been done after collection of responses. Specification of a iGLU prototype are presented in Table I.

The prototype view of proposed iGLU is shown in Figure 7. The data is collected after fixing three fingers in free space of pads. The pads are designed in such a way that emitters and detectors are placed beneath the surfaces of pads. Because of this, there will be enough free spaces between the object

TABLE I: Specification of iGLU prototype

	Channel 1	Channel 2	Channel 3
	Measured (Ideal)		
Arduino Supply	4.95V (5V)	4.96V (5V)	4.95V (5V)
Forward Voltage (Emitter)	0.96V (1.1V)	1.42V (1.5V)	1.40V (1.5V)
Forward Current (Emitter)	53.4mA (100mA)	52.8mA (60mA)	52.9mA (60mA)
Reverse Voltage (Detector)	4.25V (5V)	4.16V (5V)	4.25V (5V)
Output Current (Detector)	0.45mA (1mA)	0.5mA (1mA)	0.52mA (1mA)
Measurement range	3.2-4.68V	0.8-4.7V	0.5-4.7V
Specific Wavelength	1300nm	940nm	940nm
Spectroscopy	Absorption	Absorption	Reflectance

and sensors (emitters and detectors). Hence, the probability of a faulty measurement is minimized.

Fig. 7: Prototype view of proposed device (iGLU).

V. Proposed Machine-Learning (ML) Based Method for iGLU Calibration

Regression models are calibrated to analyze the optimized computation model for glucose estimation. The detector's output from three channels are logged as input vectors for glucose prediction. The collected data from the samples is required to convert in the form of estimated glucose values. It is necessary to develop optimal model for precise measurement and hence analysis of MAD, $mARD$, $AvgE$ and $RMSE$ are performed to ensure accuracy. The estimated and reference blood glucose concentration are calculated as BG_{Est} and BG_{Ref}, respectively. A total of 97 samples are taken for device calibration which include prediabetic, diabetic and healthy samples. The baseline characteristics of samples for calibration is represented in Table II. The proposed process flow of calibration and validation is shown in Figure 8.

TABLE II: Baseline characteristics of samples

Samples Basic Characteristics	Calibration	Validation and Testing
Age (Years)	**Gender Wise Samples**	
Male:- 22-77	Male:- 53	Male:- 64
Female:- 17-75	Female:- 44	Female:- 29
Age (Years)	**Prediabetic**	
Male:- 22-65	Male:- 18	Male:- 11
Female:- 26-75	Female:- 13	Female:- 10
Age (Years)	**Diabetic**	
Male:- 30-68	Male:- 16	Male:- 17
Female:- 30-73	Female:- 14	Female:- 11
Age (Years)	**Healthy**	
Male:- 22-65	Male:- 19	Male:- 36
Female:- 17-70	Female:- 17	Female:- 08

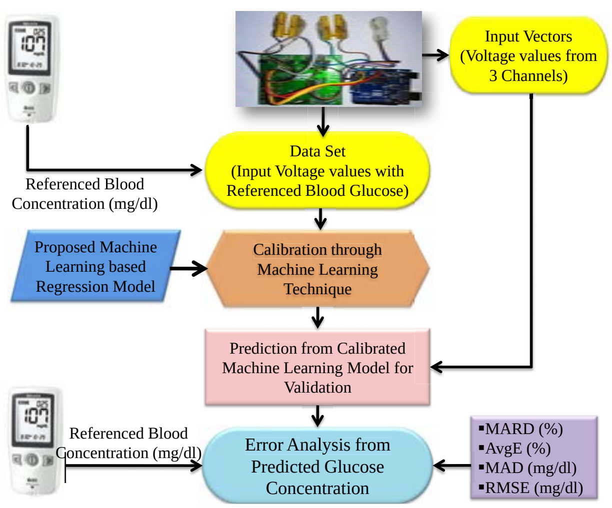


Fig. 8: The process flow of calibration and validation of proposed device (iGLU).

Deep Neural Network (DNN) based machine learning model has been applied for precise blood glucose prediction (Figure 9) [2]. Proposed DNN uses sigmoid activation functions and has been trained through Levenberg-Marquardt backpropagation algorithm [15]. In proposed model, 10 hidden neurons and 10 hidden layers are analyzed to estimate the precise blood glucose values. This model has been used to analyze the non-linear statistical data which is utilized to calibrate and validate the model for precise measurement. Here, the voltage values from three channels are used as inputs of proposed DNN model. The predicted blood glucose values are formed through the modeling of three channels voltage values. Weights of the voltage values correlate predicted glucose values to the channels data. The overall accuracy is improved using 10 hidden layers.

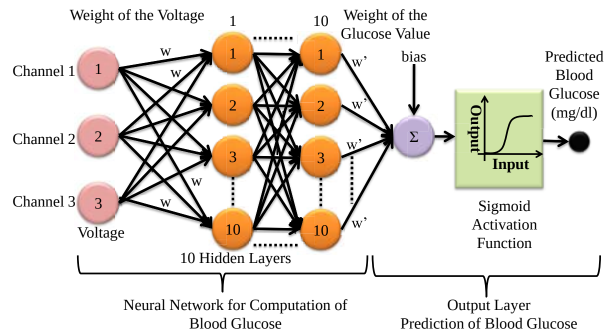


Fig. 9: The Deep Neural Network (DNN) for proposed work

The Pearson's correlation coefficient (R) is 0.953. The error analysis of calibrated machine learning models is represented in Table III.

TABLE III: Analysis of calibration and validation of proposed combination and ML model (DNN).

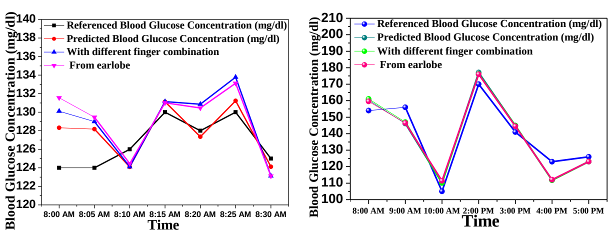
	$mARD$ (%)	$AvgE$ (%)	MAD (mg/dl)	$RMSE$ (mg/dl)
Calibration	6.65	7.30	12.67	21.95
(Validation)	**7.32**	**7.03**	**09.89**	**11.56**

VI. VALIDATION OF THE PROPOSED IGLU DEVICE

To validate and test iGLU, 93 healthy, prediabetic and diabetic samples aged 17-75 are taken following medical protocols. A total of 64 males and 29 females are identified during collection of these 93 samples. All samples are taken in fasting, postprandial and random modes. The baseline characteristics and error analysis is represented in Table II and III, respectively. A 10-fold cross validation has been performed to validate iGLU.

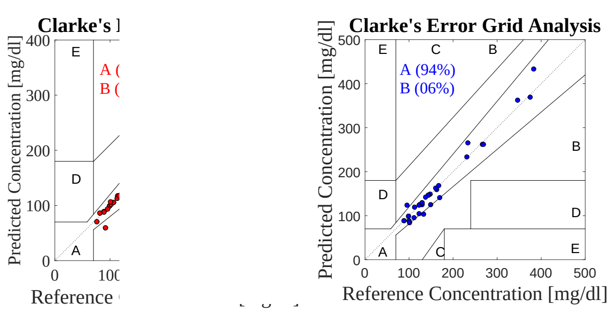
To test the device stability, an experiments have been performed from multiple measurements of same sample by couple of times. For this experimental work, a volunteer has been recruited to measure blood glucose through iGLU and invasive method with time intervals of 5 minutes.

A value of 10 mg/dl deviation are considered in observations during 7 iterations of blood glucose measurement. During analysis, 2-4 mg/dl deviation has been observed (Figure 10(a)). A different volunteer has also been taken for another experimental analysis to validate the accuracy of iGLU (Figure 10(b)). Measurement has been done with time interval of 60 minutes using 7 iterations. Variations (low to high) in reference blood glucose values between 8:00 AM-10:00 AM, 10:00 AM-2:00 PM and 2:00 PM-4:00 PM represent the glucose intakes in the form of food. During analysis, 5-10 mg/dl deviation represents the stability of iGLU. It was observed that the effect of fingers or earlobes changes is negligible. CEG analysis is used to analyze the accuracy of predicted glucose values from proposed device. CEG categorizes the devices in terms of precise measurement and elaborates the zones by the difference between referenced and predicted glucose values [27]. The predicted values are in the zone A and B; then the device will be desirable. During analysis, all predicted glucose values found in zone A and B (Figure 11).



(a) Time interval of 5 minutes (b) Time interval of 60 minutes

Fig. 10: Predicted and reference blood glucose concentration for validation of iGLU on single sample.



(a) Validation (b) Testing

Fig. 11: CEG analysis of predicted glucose values

VII. Conclusions and Future Directions

This article introduced a dual short-wave spectroscopy NIR technique based non-invasive glucose monitoring low cost (approximately 20-25 USD) device iGLU for real-life application. The error margins for iGLU are improved compared to other non-invasive approach based systems. After CEG analysis, 100% samples come in the zone A and B. During analysis of possible combinations with proposed ML model, iGLU is found more optimized compared to other measurement device.

In the future research on iGLU, we will involve more features of IoMT. Glucose-level measurement from serum is a immediate next goal to further improve accuracy of iGLU. Integration of stress measurement along with blood-glucose level is also in pipeline. A closed feedback from healthcare providers-end to the end-user side for control of effects when needed to ensure remote healthcare when there may be shortage of healthcare providers can be more effective.

Acknowledgment

The authors would like to thank Dispensary MNIT Jaipur (India). We would also thank Dr. Navneet Agrawal (diabetologist) and his team for the support at Diabetes, Obesity and Thyroid Centre Gwalior (India).

References

[1] S. Ruan, "Intelligent systems for smart health care: Leveraging information for better well-being," *IEEE Consumer Electronics Magazine*, vol. 8, no. 2, pp. 71–71, March 2019.

[2] P. Sundaravadivel, K. Kesavan, L. Kesavan, S. P. Mohanty, and E. Kougianos, "Smart-Log: A Deep-Learning Based Automated Nutrition Monitoring System in the IoT," *IEEE Trans. Consum. Electron*, vol. 64, no. 3, pp. 390–398, Aug 2018.

[3] S. P. Mohanty and E. Kougianos, "Biosensors: A Tutorial Review," *IEEE Potentials*, vol. 25, no. 2, pp. 35–40, March 2006.

[4] S. P. Mohanty, U. Choppali, and E. Kougianos, "Everything you wanted to know about smart cities: The Internet of things is the backbone," *IEEE Consumer Electronics Magazine*, vol. 5, no. 3, pp. 60–70, July 2016.

[5] P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. K. Ganapathiraju, "Everything You Wanted to Know about Smart Health Care: Evaluating the Different Technologies and Components of the Internet of Things for Better Health," *IEEE Consumer Electronics Magazine*, vol. 7, no. 1, pp. 18–28, January 2018.

[6] J. Li, P. Koinkar, Y. Fuchiwaki, and M. Yasuzawa, “A fine pointed glucose oxidase immobilized electrode for low-invasive amperometric glucose monitoring,” *Biosensors and Bioelectronics*, vol. 86, pp. 90–94, 2016.

[7] J. Y. Lucisano, T. L. Routh, J. T. Lin, and D. A. Gough, “Glucose monitoring in individuals with diabetes using a long-term implanted sensor/telemetry system and model,” *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 9, pp. 1982–1993, 2017.

[8] A. Sun, A. G. Venkatesh, and D. A. Hall, “A multi-technique reconfigurable electrochemical biosensor: Enabling personal health monitoring in mobile devices,” *IEEE Transactions on Biomedical Circuits and Systems*, vol. 10, no. 5, pp. 945–954, Oct 2016.

[9] G. Wang, M. D. Poscente, S. S. Park, C. N. Andrews, O. Yadid-Pecht, and M. P. Mintchev, “Wearable microsystem for minimally invasive, pseudo-continuous blood glucose monitoring: The e-mosquito,” *IEEE Transactions on Biomedical Circuits and Systems*, vol. 11, no. 5, pp. 979–987, Oct 2017.

[10] M. M. Ahmadi and G. A. Jullien, “A wireless-implantable microsystem for continuous blood glucose monitoring,” *IEEE Transactions on Biomedical Circuits and Systems*, vol. 3, no. 3, pp. 169–180, June 2009.

[11] G. Acciaroli, M. Vettoretti, A. Facchinetti, G. Sparacino, and C. Cobelli, “Reduction of blood glucose measurements to calibrate subcutaneous glucose sensors: A bayesian multiday framework,” *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 3, pp. 587–595, 2018.

[12] I. Pagkalos, P. Herrero, C. Toumazou, and P. Georgiou, “Bio-inspired glucose control in diabetes based on an analogue implementation of a β-cell model,” *IEEE Transactions on Biomedical Circuits and Systems*, vol. 8, no. 2, pp. 186–195, April 2014.

[13] P. P. Pai, A. De, and S. Banerjee, “Accuracy enhancement for noninvasive glucose estimation using dual-wavelength photoacoustic measurements and kernel-based calibration,” *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 1, pp. 126–136, 2018.

[14] M. Yamaguchi, M. Mitsumori, and Y. Kano, “Noninvasively measuring blood glucose using saliva,” *IEEE Engineering in Medicine and Biology Magazine*, vol. 17, no. 3, pp. 59–63, May 1998.

[15] K. Song, U. Ha, S. Park, J. Bae, and H. J. Yoo, “An impedance and multi-wavelength near-infrared spectroscopy ic for non-invasive blood glucose estimation,” *IEEE Journal of Solid-State Circuits*, vol. 50, no. 4, pp. 1025–1037, April 2015.

[16] W.-C. Shih, K. L. Bechtel, and M. V. Rebec, “Noninvasive glucose sensing by transcutaneous raman spectroscopy,” *Journal of biomedical optics*, vol. 20, no. 5, p. 051036, 2015.

[17] C. W. Pirnstill, B. H. Malik, V. C. Gresham, and G. L. Coté, “In vivo glucose monitoring using dual-wavelength polarimetry to overcome corneal birefringence in the presence of motion,” *Diabetes technology & therapeutics*, vol. 14, no. 9, pp. 819–827, 2012.

[18] E. Monte-Moreno, “Non-invasive estimate of blood glucose and blood pressure from a photoplethysmograph by means of machine learning techniques,” *Artificial intelligence in medicine*, vol. 53, no. 2, pp. 127–138, 2011.

[19] S. Habbu, M. Dale, and R. Ghongade, “Estimation of blood glucose by non-invasive method using photoplethysmography,” *Sādhanā*, vol. 44, no. 6, p. 135, 2019.

[20] S. Sharma, M. Goodarzi, L. Wynants, H. Ramon, and W. Saeys, “Efficient use of pure component and interferent spectra in multivariate calibration,” *Analytica chimica acta*, vol. 778, pp. 15–23, 2013.

[21] P. Jain, R. Maddila, and A. M. Joshi, “A precise non-invasive blood glucose measurement system using NIR spectroscopy and Hubers regression model,” *Optical and Quantum Electronics*, vol. 51, no. 2, p. 51, 2019.

[22] Y. Uwadaira, A. Ikehata, A. Momose, and M. Miura, “Identification of informative bands in the shortwavelength nir region for non-invasive blood glucose measurement,” *Biomedical Optics Express*, vol. 7, no. 7, pp. 2729–2737, 2016.

[23] W. Zhang, R. Liu, W. Zhang, H. Jia, and K. Xu, “Discussion on the validity of nir spectral data in non-invasive blood glucose sensing,” *Biomedical optics express*, vol. 4, no. 6, pp. 789–802, 2013.

[24] S. Haxha and J. Jhoja, “Optical based noninvasive glucose monitoring sensor prototype,” *IEEE Photonics Journal*, vol. 8, no. 6, pp. 1–11, 2016.

[25] M. Golic, K. Walsh, and P. Lawson, “Short-wavelength near-infrared spectra of sucrose, glucose, and fructose with respect to sugar concentration and temperature,” *Applied spectroscopy*, vol. 57, no. 2, pp. 139–145, 2003.

[26] P. Jain and S. Akashe, “Analyzing the impact of bootstrapped adc with augmented nmos sleep transistors configuration on performance parameters,” *Circuits, Systems, and Signal Processing*, vol. 33, no. 7, pp. 2009–2025, 2014.

[27] W. L. Clarke, “The original Clarke error grid analysis (EGA),” *Diabetes technology & therapeutics*, vol. 7, no. 5, pp. 776–779, 2005.

About the Authors

Prateek Jain is a Research Scholar in ECE department of MNIT, Jaipur, India. He can be contacted at: prtk.ieju@gmail.com.

Amit M. Joshi is an Assistant Professor in Department of ECE, MNIT, Jaipur, India. He can be contacted at: amjoshi.ece@mnit.ac.in.

Saraju P. Mohanty is the Editor in Chief of the IEEE Consumer Electronics Magazine and Professor in the Department of Computer Science and Engineering (CSE), University of North Texas (UNT), Denton, TX, USA. Contact him at Saraju.Mohanty@unt.edu.