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

Prateek Jain and Amit M. Joshi
Malaviya National Institute of Technology

Saraju P. Mohanty
University of North Texas

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

The smart healthcare system is comprised of ambient intelligence, quality of service, while providing support for continuous monitoring of health conditions.[1,2] This system can be useful for remote monitoring of diabetic patients with low cost and rapid diagnosis (See Figure 1).[3] Traditional blood glucose measurement is unable to serve everyone's need at a remote location. Despite having good diagnostic centers for clinical test facilities in an urban area, medical services are not approachable to everyone at remote locations.[4,5] It is necessary to monitor blood glucose of diabetic patients where diagnosis facilities are not easily

Digital Object Identifier 10.1109/MCE.2019.2940855
Date of current version 6 December 2019.

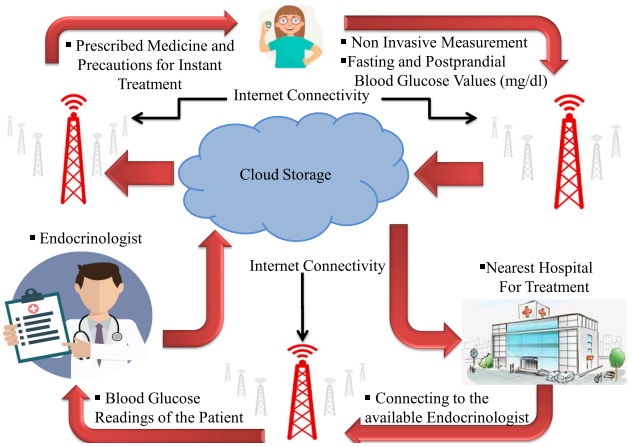


Figure 1. Blood glucose diagnosis in smart healthcare.

accessbile. The instant diagnose of blood glucose and frequent monitoring are the recent challenges in smart healthcare.

IoMT enabled noninvasive can be useful for rapid monitoring and interaction of endocrinologists with the remote located diabetic patients. In this platform, patients measure their glucose without pricking blood and directly store glucose data in the cloud that endocrinologist can access. The ubiquity of diabetic patients has doubled from 2010 all 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 of their glucose level with frequent monitoring. Invasive methods for glucose measurement is not advisable in cases of continuous monitoring.

STATE-OF-ART IN BLOOD GLUCOSE-LEVEL MEASUREMENT

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

Invasive Methods

An amperometric glucose monitoring biosensor has been proposed using a glucose oxidase immobilized electrode, to be inserted in to the skin.[6] A fully implanted first-generation prototype sensor has been presented for long-term monitoring of subcutaneous tissue glucose.[7]

Minimally Invasive Methods

Implantable biosensors have been deployed for CGM.[8,10] Wearable minimally invasive microsystems have been explored for glucose monitoring.[9] It is possible to reduce the frequency of calibration of a minimally invasive Dexcom sensor.[11] An artificial pancreas has been presented to control diabetes.[12] But, the semi-invasive approaches may not be useful for real-time CGM due to inconveniences and high cost.

Noninvasive Methods

Photoacoustic spectroscopy has been introduced for noninvasive painless glucose measurement.[13] The use of LASER (Light Amplification by

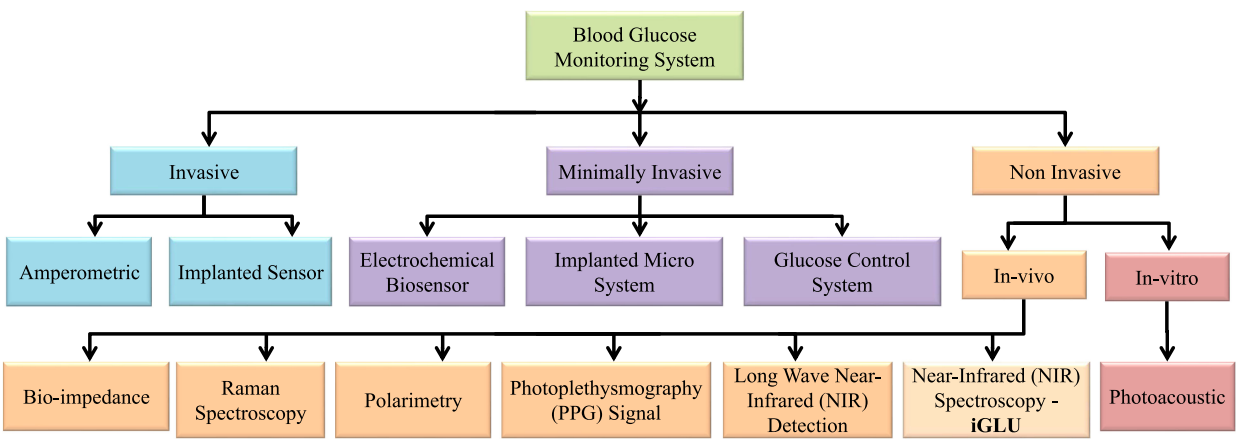


Figure 2. Overview of various blood glucose-level measurement devices or systems.

Stimulated Emission of Radiation) 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 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 but it is not portable.[16] Glucose measurement is possible from an anterior chamber of the eye, which limits its usage of continuous monitoring.[17] Blood glucose has been estimated using photoplethysmography (PPG) signals.[18,19]

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

Prior approaches in glucose monitoring include both wearable and nonwearable. Raman spectroscopy, photoacoustic spectroscopy, and invasive approach based systems are not wearable. Minimally invasive devices, which have been discussed, are implantable. Other approaches based on noninvasive devices are wearable. Here, iGLU is a noninvasive, optical detection based wearable device for CGM with IoMT framework.

Consumer Electronics for Glucose Monitoring

Several devices have been developed for noninvasive blood glucose measurement. Some products such as glucotrack, glutrac, glucowise, DiaMon Tech, and devices from CNOGA medical are not commercialized. Glutrac is a multiparameter health test device with smart healthcare. However, they have limitations in terms of precise measurement. The cost of the product is also high, which is in the range of $300 to $400 USD.

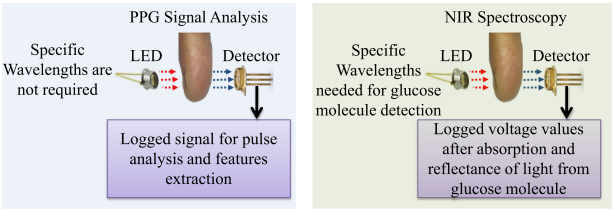


Figure 3. PPG signal versus NIRS based glucose estimation.

A NOVEL WEARABLE FOR CONTINOUS BLOOD GLUCOSE MONITORING - iGLU

Non-invasive measurement reduces the possibility of blood-related diseases. However, the existing approaches have limitations such as large setup, measuring object, and skin properties (including dielectric constant and sweat level). Therefore, portable noninvasive precise glucose measurement devices for continuous monitoring are needed.[21]

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 the cloud for future use? 2) Can we have a device that can perform automatically to avoid hassle and risky finger pricking all the time monitoring is needed?

The "Intelligent Glucose Meter" (i.e., iGLU) performs noninvasive, precise, painless, low-cost CGM at the user-end, and stores the data on cloud in an IoMT framework (See Figure 4). The contributions of this article to smart healthcare include the following:

1) A novel accurate noninvasive glucometer that uses short NIR waves with absorption and reflectance of light using specific wavelengths (940 and 1,300 nm) has been introduced. The wavelengths are judiciously selected after experimental analysis.
2) A novel accurate ML-based method for glucose sensor calibration has been presented with calibrated and validated healthy, prediabetic, and diabetic samples.
3) The proposed noninvasive device has been integrated in IoMT framework with cloud access by both the patient and doctor for

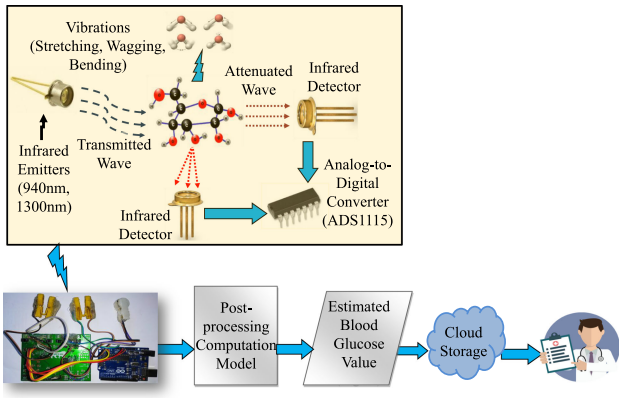


Figure 4. Conceptual overview of iGLU.

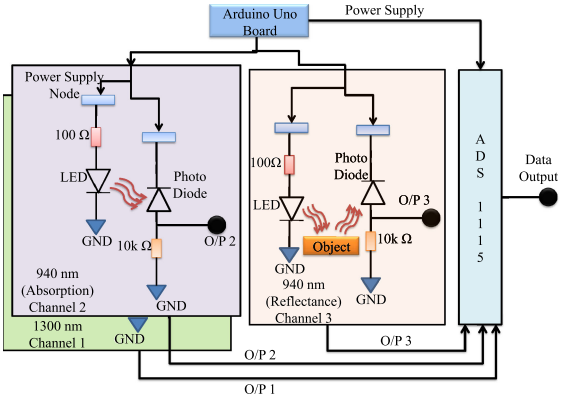


Figure 6. Circuit topology of proposed device.

data (blood glucose values) storage, patient monitoring, and treatment.

DESIGN AND PROTOTYPING of iGLU

The proposed device based on NIR spectroscopy uses two short wavelengths in three channels. Each channel is embedded with emitters and detectors of specific wavelengths for optical detection. The data are collected and serially processed by 16 bit ADC with sampling rates of 128 samples/s. The flow of data acquisition for iGLU is shown in Figure 5.

Approach for Glucose Molecule Detection

Glucose molecule vibrates according to its atomic structure at specific wavelengths. It is observed that absorbance and reflectance are sharper and stronger in short wave NIR regions.[22] The absorption peak of glucose spectra at 1,314 nm has been analyzed.[23] The noninvasive blood glucose measurement using 850, 950, and 1,300 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]

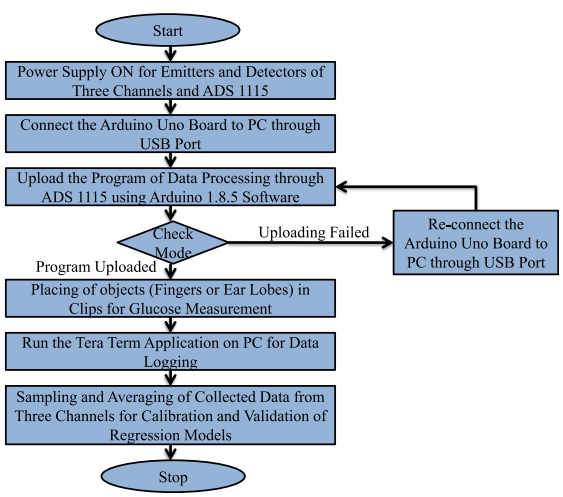


Figure 5. Process flow data acquisition for iGLU.

Proposed Module for Data Acquisition

A 2-Layer PCB has been developed to embed infrared emitters (MTE1300W for 1,300 nm, TSAL6200 for 940 nm, and TCRT1000 for 940 nm) and detectors (MTPD1364D for 1,300 nm, 3004MID for 940 nm, and TCRT1000 for 940 nm) (See Figure 6). The hardware is designed for data acquisition from emitters, detectors, and ADC with 5-V dc supply. Accordingly, compatible passive components have been chosen. 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 is used to convert the data (in Volts) from all channels in decimal form. The noise power and signal-to-noise ratio (SNR) have also been found at 0.08 and 25.2 dB, respectively, which show the minimum noise level.

A Specific Prototype of the iGLU

Absorption and reflectance at 940 nm and absorption at 1,300 nm are used for the detection of the glucose molecules. The detector's voltage depends on received light intensity.

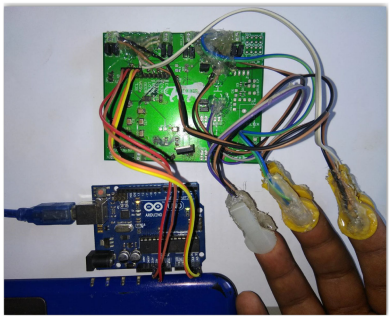


Figure 7. Prototype of proposed iGLU.

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 noninvasive results. The reading is taken as referenced blood glucose values (mg/dl). During the process, optical responses through detectors have been collected from three channels, simultaneously. The channels data are collected in the form of voltages from three detectors. These voltages correspond to referenced blood glucose concentration. These voltage values are converted into decimal form using four-channel ADC.[26] Coherent averaging has been done after collection of responses. Specifications of a iGLU prototype (See Figure 7) are presented in Table 1.

The data in iGLU are 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 and sensors (emitters and detectors). Hence, the probability of a faulty measurement is minimized.

A ML-BASED METHOD FOR IGLU CALIBRATION

Regression models are calibrated to analyze the optimized computation model for glucose estimation (See Figure 8). The detector's output from three channels are logged as input vectors for glucose prediction. To develop optimal models for precise measurement, various error analysis performed to ensure

Table 1. Specification of iGLU prototype.

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

accuracy using the estimated and referenced blood glucose concentrations. A total of 97 samples are taken for device calibration which include prediabetic, diabetic, and healthy samples (See Table 2).

A deep neural network (DNN) model has been applied for precise blood glucose prediction (see Figure 9).[2] The DNN uses sigmoid activation functions and has been trained through Levenberg–Marquardt backpropagation.[15] In the DNN model, 10 hidden neurons and 10 hidden layers have been used. The nonlinear statistical data has been used to calibrate and validate the model for

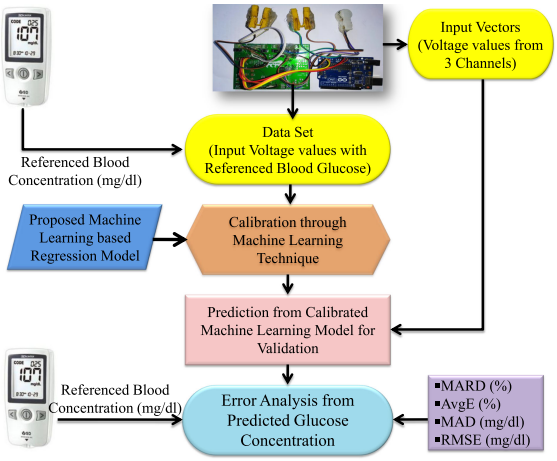


Figure 8. Process flow of calibration and validation of iGLU.

Table 2. 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

precise measurement. The voltage values from three channels are used as inputs of the 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 Pearson's correlation coefficient (R) is 0.953. The error analysis of calibrated ML models is represented in Table 3.

VALIDATION OF THE IGLU

To validate iGLU, 93 healthy, prediabetic, and diabetic samples, aged 17–75, were taken following medical protocols. A total of 64 males and 29 females are identified during collection of these

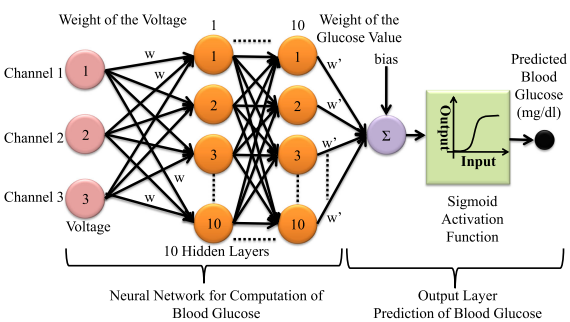


Figure 9. DNN model integrated in iGLU.

93 samples. All samples are taken in fasting, post-prandial, and random modes. The baseline characteristics and error analysis are represented in Tables 2 and 3, respectively. A 10-fold cross validation were performed to validate iGLU.

To test the device stability, experiments have been performed from multiple measurements of the same sample. For this experiment blood glucose has been measured using both iGLU and invasive method with time intervals of 5 min from one volunteer.

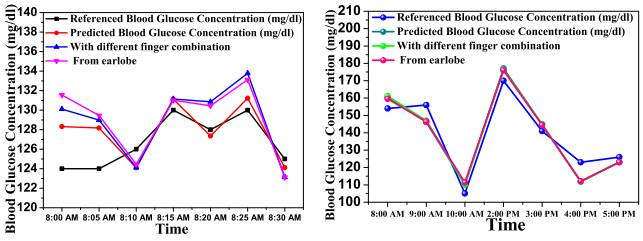
A value of 10 mg/dl deviation are considered in observations during seven iterations of blood glucose measurement. During analysis, 2–4 mg/dl deviation has been observed (see Figure 10(a)). A different volunteer has also been taken for another experimental analysis to validate the accuracy of iGLU (see Figure 10(b)). Measurement has been done with time intervals of 60 min using seven iterations. Variations (low to high) in referenced 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 (Clarke Error Grid) analysis is used to analyze the accuracy of predicted glucose values from iGLU. CEG categorizes the devices in terms of precise measurement and elaborates the zones by the difference between referenced and predicted glucose values.[27] If the predicted values are in zones A and B, then the device will be desirable. During analysis, all predicted glucose values are found in zones A and B (see Figure 11).

CONCLUSION

This article introduced a dual short-wave NIR based noninvasive low cost (approximately $20–$25 USD) device iGLU for CGM. The error margins for iGLU are improved compared to other noninvasive systems. CEG analysis shows iGLU is 100% accurate. The future versions of iGLU will integrate more features of IoMT. Glucose-level measurement from serum is an immediate next step for further advancement of iGLU.

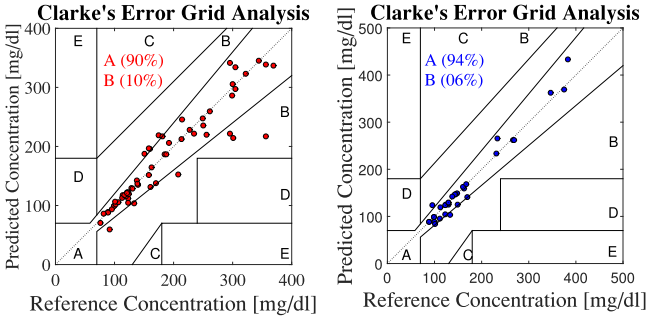
Table 3. Analysis of calibration and validation of proposed DNN models.

	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



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

Figure 10. Predicted and reference blood glucose concentration for validation of iGLU on single sample. (a) Time interval of 5 minutes. (b) Time interval of 60 minutes.



(a) Validation (b) Testing

Figure 11. CEG analysis of predicted glucose values. (a) Validation (b) Testing.

ACKNOWLEDGMENTS

We thank Dispensary and Materials Research Center (MRC) at the MNIT Jaipur (India). We thank Dr. Navneet Agrawal and his team at the Diabetes, Obesity, and Thyroid Centre Gwalior (India). We thank Ministry of Human Resources and Development (MHRD), Govt. of India for its support.

REFERENCES

1. S. Ruan, "Intelligent systems for smart health care: Leveraging information for better well-being," *IEEE Consum. Electron. Mag.*, vol. 8, no. 2, pp. 71–71, Mar. 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, Mar. 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 Consum. Electron. Mag.*, vol. 5, no. 3, pp. 60–70, Jul. 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 Consum. Electron. Mag.*, vol. 7, no. 1, pp. 18–28, Jan. 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 Bioelectron.*, 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 Trans. Biomed. Eng.*, vol. 64, no. 9, pp. 1982–1993, Sep. 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 Trans. Biomed. Circuits Syst.*, 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 Trans. Biomed. Circuits Syst.*, 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 Trans. Biomed. Circuits Syst.*, vol. 3, no. 3, pp. 169–180, Jun. 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 Trans. Biomed. Eng.*, vol. 65, no. 3, pp. 587–595, Mar. 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 Trans. Biomed. Circuits Syst.*, vol. 8, no. 2, pp. 186–195, Apr. 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 Trans. Instrum. Meas.*, vol. 67, no. 1, pp. 126–136, Jan. 2018.
14. M. Yamaguchi, M. Mitsumori, and Y. Kano, "Noninvasively measuring blood glucose using saliva," *IEEE Eng. Medicine Biol. Mag.*, 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 J. Solid-State Circuits*, vol. 50, no. 4, pp. 1025–1037, Apr. 2015.
16. W.-C. Shih, K. L. Bechtel, and M. V. Rebec, "Noninvasive glucose sensing by transcutaneous raman spectroscopy," *J. Biomed. Opt.*, vol. 20, no. 5, 2015, Art. no. 051036.
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 Technol. 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," *Artif. Intell. Med.*, 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 Huber's regression model," *Opt. Quantum Electron.*, 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," *Biomed. Opt. 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," *Biomed. Opt. Express*, vol. 4, no. 6, pp. 789–802, 2013.
24. S. Haxha and J. Jhoja, "Optical based noninvasive glucose monitoring sensor prototype," *IEEE Photon. J.*, vol. 8, no. 6, pp. 1–11, Dec. 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," *Appl. Spectrosc.*, 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, Syst. Signal Process.*, vol. 33, no. 7, pp. 2009–2025, 2014.
27. W. L. Clarke, "The original Clarke error grid analysis (EGA)," *Diabetes Technol. Therapeutics*, vol. 7, no. 5, pp. 776–779, 2005.

Prateek Jain is a research scholar in the Department of ECE (Electronics & Communication Engineering), MNIT, Jaipur, India. Contact him at prtk.ieju@gmail.com.

Amit M. Joshi is an assistant professor in the Department of ECE, MNIT, Jaipur, India. Contact him at amjoshi.ece@mnit.ac.in.

Saraju P. Mohanty is a professor in the Department of Computer Science and Engineering, University of North Texas, Denton, TX, USA. Contact him at Saraju.Mohanty@unt.edu.