iGLU 2.0: A New Wearable for Accurate Non-Invasive Continuous Serum Glucose Measurement in IoMT Framework

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***Abstract*—People around the globe rely on their blood samples for their glucose level measurement. There is a demand for non-invasive, precise and cost-effective solutions to monitor blood glucose level and control of diabetes. Serum glucose is an accurate blood glucose measurement method in comparison to capillary glucose measurement. Presently, the serum glucose is measured through laboratory setup with an invasive approach. The invasive method is painful and is not suitable for continuous glucose measurement. In this paper, we propose a novel wearable non-invasive consumer device (called iGLU 2.0) which can be used by consumers for accurate continuous blood glucose monitoring. This device uses a novel short near infrared (NIR) spectroscopy developed by us. It is incorporated with Internet-of-Medical-Things (IoMT) for smart healthcare where the healthcare data is stored on the cloud and is accessible to the users and caregivers. Analysis of the optimized regression model is performed and the system is calibrated and validated through healthy, prediabetic and diabetic patients. The robust regression models of serum glucose level is then deployed as the mechanism for precise measurement in iGLU 2.0. The performance of iGLU 2.0 is validated with the prediction of capillary blood glucose using Average Error (AvgE) and Mean Absolute Relative Difference (mARD) which are calculated as 6.09% and 6.07%, respectively, whereas for serum glucose, AvgE and mARD are estimated as 4.88% and 4.86%, respectively.**

***Index Terms*—Smart home, smart healthcare, smart wearable, Internet-of-Medical-Things (IoMT), glucose measurement, capillary and serum glucose, non-invasive device, near infrared (NIR) spectroscopy, regression model, deep neural network (DNN)**

I. Introduction

The healthcare has evolved from traditional to telemedicine, connected-health (cHealth), e-health, mobile-health (mHealth), to smart health (sHealth) [1]. The growth of Information and Communication Technologies and IoT has made the great impact on healthcare sector. Smart healthcare system helps to capture the data of the patient through smart sensors to assist them from healthcare provider without any geographical barrier. Overall smart healthcare is evolving with the help of healthcare Cyber-Physical System (H-CPS) that integrates IoMT, electronic health record (EHR) which is essentially e-health, and artificial intelligence (AI) obtained from sensor data as well as EHR [2]. The smart healthcare is in demand where doctors and patients are connected remotely for the instant treatment [3]. The Internet of Medical Things (IoMT) has revolutionized the solutions of smart healthcare with quality of care and proper diagnosis [4]. The continues monitoring allows the patient to determine the critical conditions for possible corrective actions. The real-time access of the health records is useful to perform the health analysis and subsequent impact over the society. The point of care service and medication has become easier with effective and intelligent consumer electronics devices in smart healthcare system.

Diabetes is one of the prominent diseases around the world. Total 422 million diabetic people have been reported in 2019 [5], [6]. Diabetes is a condition where the insulin of the body is destructed and cells and muscles are unable to consume the insulin properly [7]. Type-1 Diabetes patient faces the difficulty to control the blood sugar because of insufficient insulin generation. However, Type-2 Diabetes is most common among the people where the body is able to produce limited insulin only. There are higher chances of heart and kidney failures as well as blindness if the diabetes is not controlled for a long time. Hence, it is necessary to have the smart solution for instant blood glucose diagnosis and frequent monitoring for diabetes patients (see Fig. 1) to improve quality of life.

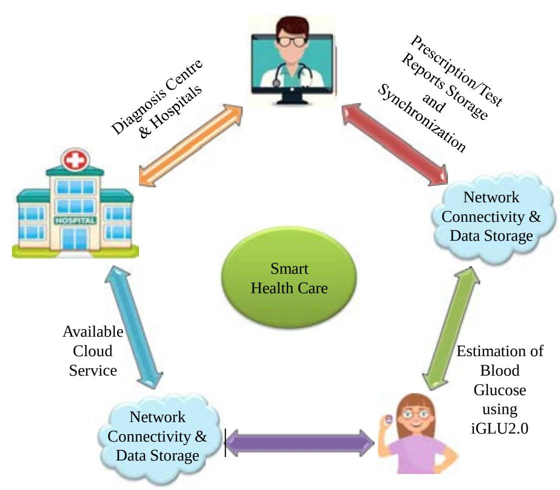

Fig. 1. Glucose Measurement in smart healthcare.

The overall smart healthcare flow with glucose diagnosis is shown in Fig. 1. The glucose value is measured and the

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data is stored at cloud for the doctor analysis. The rapid serum glucose measurement (as compared to traditional blood glucose measurement) is the modern challenge in the smart healthcare system with continuous monitoring.

The current paper presents a new wearable glucometer which can measure the blood glucose level in a non-invasive fashion. The proposed non-invasive blood glucose measurement is based on the principle of Near-Infrared (NIR) optical spectroscopy whereas the other existing glucose measurement wearable which use photoplethysmogram (PPG) or other spectroscopy techniques have serious accuracy issues. The acquired data is further processed using regression model to estimate the glucose value. The proposed wearable glucose measurement device provides precise serum glucose level using absorption and reflectance based dual NIR spectroscopy and calibrated machine learning models.

The rest of the paper is presented in following manner. The state of art glucose measurement is elaborated in Section II. Our vision for non invasive glucose measurement along with its control is covered in Section III. The novel contribution is detailed in Section IV. Section V explains the machine learning models for serum and capillary glucose measurement. The proposed iGLU 2.0 device is described for serum glucose detection and is presented in Section VI. The error analysis is performed with analytical modelling in Section VII.

II. The State-of-Art in Glucose Measurement and its Advancement through the Current Paper

A. Consumer Electronics for Smart Healthcare

The quality of life in smart healthcare is improved tremendously through consumer electronics, however the precision and reliability are the important factors for the different applications. The wearable medical devices, such as patches, glasses, wrist gadgets, badges, rings, and bracelets [8], has enabled easier ways of monitoring the health in daily life. There has been substantial research carried out in smart healthcare for consumer electronics on assisting visually impaired individuals [9], [10] and detection of fall of elderly [11]. In addition, consumer electronics in smart healthcare domain deal with monitoring of physiological signals such as electroencephalogram (EEG) [12], Electrocardiography (ECG) [13]–[15], heart rate [16]. The proposed iGLU 2.0 of the current article is a consumer electronics wearable device and it is integrated with IoMT framework in smart healthcare system. It is useful to improve the quality of life through daily monitoring of the diet at smart homes.

Non-Communicable Disease (NCD) is mainly defined as noninfectious condition which is gradually being developed over the period of time termed as chronic disease [17]. Diabetes is one of NCD along with other such as cancer, cardiovascular disease, and chronic respiratory disease [18]. The continuous monitoring and telemedicine plays a significant role for the control of such NCD in smart healthcare system. The people needs to put concious efforts using various self-care device to control them in daily life [19]. The non-invasive approach is useful in smart healthcare to eliminate the process of pricking in the body which helps for continuous health monitoring [20]. Non-invasive approaches of measurement are more advanced compared to the current invasive method to make the painless device. The portable system of measurement of the non-invasive measurement device is desirable for smart healthcare system. The optical method is more reliable, cost-efficient and accurate according to the analysis of researchers. There are varieties of various optical techniques for non-invasive measurement such as photoacoustic spectroscopy, polarimetric, near infer-red spectroscopy, Raman spectroscopy and scattering spectroscopy. For the smart healthcare, it is desirable to have portable and wearable device to be useful in day to day life. In this way, improvement of the accuracy and reliability of these devices have been considered as essential objectives. The idea is to develop for the self-monitoring system which is to be embedded for continuous monitoring in smart home environment. Researchers have developed a flexible textile-based biosensor which is useful to investigate the glucose level.

B. Consumer Electronics for Glucose-Level Monitoring in Smart Healthcare

There are a number of non-invasive blood glucose measurement devices developed till date. Some devices are not effective due to their accuracy issues. There are few adhesive and disposable solutions are available for the continuous monitoring. These can be categorized as either semi invasive or minimum invasive solutions to monitor the glucose level. The non-invasive stripless solution is also available for continuous glucose monitoring. There are fluorescent technique based solution to monitor the glucose value but it is not much popular. These devices have limited accuracy for glucose level measurement. Many approaches have failed due to environmental constraints, error in the measurement due to body temperature variations, interstitial fluids, body pressure, sweat and body water variations. Because of these constraints, most non-invasive devices are unable to provide an accurate measurement. These devices are also costly in the range of 300-400 USD. There is still not any cost-effective and precise solution available in the consumer electronics market.

C. Prior Works on Noninvasive Glucose Level Monitoring

Various invasive, semi-invasive and non-invasive approaches have been explored for glucose measurement [21]. The non-invasive glucose measurement is performed by wearable using saliva, skin, sweat and retina. However, the current paper presents the non-invasive glucometer and can be implemented as wearable consumer electronics.

Nanoparticles on alkali anodized steel electrode have been presented for glucose measurement through saliva [22]. Optical biosensor have been presented for glucose measurement using saliva [23]. Glucose measurement has also been done using impedance spectroscopy through the skin [24], [25]. Electrical properties of skin, sweat and saliva vary according to person. So, this approach will not be reliable for glucose measurement.

Non-invasive glucose measurement approach through retina has also been represented for precise glucose detection [26].

Such non-invasive approach is not desirable for frequent monitoring [27]. Raman spectroscopy has been preented for precise glucose measurement [28]. The implemented setup occupied a large area and will not be portable.

Most of non-invasive measurement techniques have limited precision level. Hence, the device iGLU 1.0 has been represented for non-invasive capillary glucose measurement [29]. Serum glucose is considered to be more accurate than capillary blood glucose as per medical aspects. Therefore, it is necessary to design serum glucose based non-invasive portable device to accurately measure glucose level to advance the state-of-the-art and improve quality of life, which is the scope of the current papers.

III. Our Vision of Noninvasive Glucose Level Measurement and Control using New Wearable

The privacy and security threats of the medical devices are crucial aspect for any IoMT framework. The wireless communication and control of wearable iGLU 2.0 devices has several security vulnerability and are defined in Fig. 2. The hardware security of devices are imperative because they are the basic components of connected health system. The data integrity over the medical information is another significant security layer. The data of all patients are stored at cloud server hence privacy and security of health data records are also at most important. The access control and authentication of end users of the network is also vital as they have to perform monitoring and treatment of the patient.

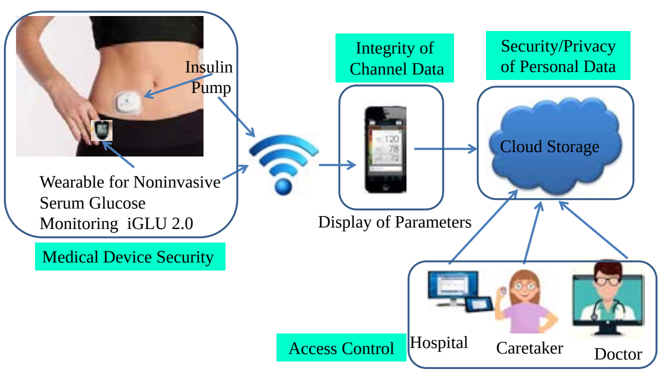


Fig. 2. Our Long-Term Vision of Security-Assured Noninvasive Glucose-Level Measurement and Control.

A. Our Vision of Noninvasive Glucose Level Measurement using New Wearable

The blood glucose level of the particular person in each prandial state is analysed using CGM. It may be helpful for the individual to control the glucose value by insulin secretion, physical activity and after taking medicines. Type 1 diabetic patients can also define their insulin dosage with help of CGM. This may decrease the excessive insulin secretion in their body. The diet plan can be controlled with frequent glucose monitoring. As the average value of glucose is identified over a long period, it is helpful to measure the glucose values over longer period of the time to help in determining the glycated haemoglobin. Infrared spectroscopy (IR spectroscopy or Vibrational Spectroscopy) involves the interaction of infrared radiation with matter. It covers scattering, absorption and reflection spectroscopy. The absorption of IR waves causes the generation of vibrations of the molecular atom and causes of band spectrum which are usually expressed by wavenumber cm^{-1}. In NIR spectroscopy, the light in the range of $(700nm - 2500nm)$ is passed through the object (earlobe or finger). The passed light through the finger or earlobe interacted with the components of blood and gets reflected, absorbed and scattered. The penetration depth will be varied with a change in wavelength. The value of absorption coefficient depends upon the change in glucose concentration. The value of glucose concentration in blood vessel could be indicated due to change in intensity of transferred light through the vessel. The change in glucose concentration is measured through light detector. NIR spectroscopy would also help for the wearable device as glucose molecule detection is more precise in this range. In current paper, iGLU 2.0 is proposed for serum glucose monitoring using short-wave NIR spectroscopy with calibration and validation using machine learning models.

B. NIR Spectroscopy versus other Non-Invasive Approaches

Glucose measurement has been done using various non-invasive approaches, such as impedance spectroscopy, NIR light spectroscopy and PPG signal analysis [30]. But, apart from optical detection, other techniques have failed to achieve the accuracy. PPG signal analysis is based on extracted features of logged signal which is not based on principle of glucose molecular detection [31], [32]. To overcome these limitations, Sharma et.al also discussed about optical detection using long NIR wave which is not capable to detect the glucose molecules beneath the skin as it has shallow penetration [33]. Therefore, small NIR wave has been chosen for real-time glucose detection [34], [35].

C. Serum Glucose is More Accurate than Capillary Glucose

In the case of invasive approaches, serum glucose and capillary glucose level are being analyzed for precise blood glucose values. Capillary glucose can be estimated instantly but serum glucose couldn't be identified instantly due to certain processes. However, it is clinically observed that the capillary glucose level is always higher than serum glucose which is not being considered actual blood glucose ever. Hence, there is a tradeoff between both approaches. But, serum glucose has always been recommended for diagnosis as an accuracy point of view. Therefore, serum glucose is always being reliable compared to capillary glucose for medication.

IV. Novel Contributions of the Current Paper to the State-of-Art

The serum glucose measurement requires well equipped laboratory and storage at specific (frozen) temperature to extract the serum. Therefore, it is costly and time consuming process for the instant diagnosis. The paper focuses on development of non-invasive continuous glucose measurement solution for smart healthcare. The proposed solution provides the accurate serum glucose values for all types of user, such as diabetic, pre-diabetic, and healthy.

The main challenge is to design a wearable device to measure the accurate blood serum glucose measurement. The design of data acquisition mechanism which is required for continuous glucose measurement. The development of accurate models for the precise prediction of serum glucose is also challenge. The proposed device should be able to measure the accurate measurement for pre diabetic and diabetic patients.

To mitigate the above problems, we proposed non-invasive serum glucose measurement device called iGLU 2.0 in this paper to determine accurate serum glucose. It is cost effective solution and is also integrated with IoMT framework for data storage on the cloud. The device is helpful to measure continuous values of serum glucose. The process flow of proposed iGLU 2.0 is defined in Fig. 3.

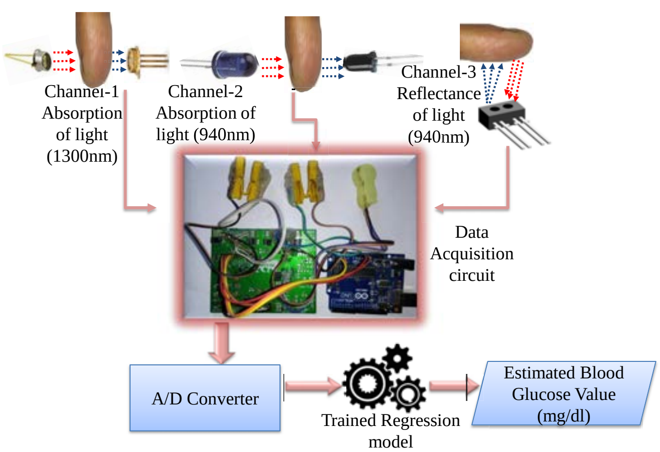


Fig. 3. Top level representation of proposed device (iGLU 2.0).

Novel contribution in current paper include the following:

1) An unique dual NIR spectroscopy that involves absorption and reflection spectroscopy of 940 nm, and absorption spectroscopy of 1300 nm has been proposed for accurate detection of serum glucose level.
2) Novel deep neural network (DNN) and polynomial regression models have been developed based on real-life serum data and dual-NIR spectroscopy for precise glucose level prediction.
3) The acquisition module has been designed to collect blood glucose measurement samples using NIR LEDs of 940 nm and 1300 nm spectral wavelength.
4) The continuous glucose measurement system has been developed which is able to measure the serum glucose measurement from 80-420 mg/dl for all type of diabetic people.

V. Machine Learning (ML) Models for Blood Glucose Level Calculation from the NIR Signal

The regression models are applied to estimate the glucose concentrations for validation. The value of each sample is converted for the calibration to have the precise measurement. There are 113 samples for capillary glucose and 74 samples of serum glucose to the calibration of the device which are from prediabetic, diabetic and healthy subjects. The baseline characteristics are defined in Table I.

TABLE I
Baseline characteristics of collected samples for calibration, validation and testing

Samples Basic Characteristics	Capillary Glucose	Serum Glucose	Capillary Glucose	Serum Glucose
	Calibration		**Validation and Testing**	
Age (Years)		**Prediabetic Samples**		
Male:-18-80	Male:-23	Male:-13	Male:-18	Male:-10
Female:-17-75	Female:-20	Female:-16	Female:-16	Female:-09
Age (Years)		**Diabetic Samples**		
Male:-18-80	Male:-30	Male:-18	Male:-14	Male:-15
Female:-17-75	Female:-19	Female:-12	Female:-12	Female:-12
Age (Years)		**Healthy Samples**		
Male:-18-80	Male:-09	Male:-08	Male:-07	Male:-05
Female:-17-75	Female:-12	Female:-07	Female:-07	Female:-08
Age (Years)		**Total Samples**		
Male:-18-80	Male:-62	Male:-39	Male:-39	Male:-30
Female:-17-75	Female:-51	Female:-35	Female:-35	Female:-29

The process steps for calibration and validation are shown in Fig. 4. The mARD, AvgE, Mean absolute deviation (MAD) and Root Mean Square Error (RMSE) are computed to estimate the performance.

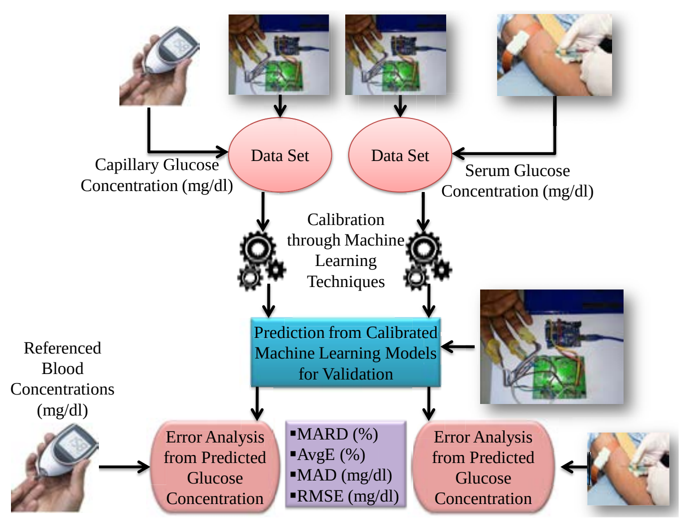


Fig. 4. The process flow for calibration and validation of proposed device.

A. Proposed Method 1: Proposed Deep Neural Network (DNN) for Glucose Sensor Calibration

Several machine learning-based computation models have been examined to get optimized regression method in terms of precise measurement. The fitting model of DNN is used for the prediction of capillary and serum glucose [25]. Sigmoid activation functions have been applied for the proposed DNN models. The model are trained through Levenberg-Marquardt backpropagation algorithm [36]. The diagram of DNN model is presented in Fig. 5. Overall accuracy of the DNN model was observed to be best with 10 hidden layers. The error analysis for different layers is shown in Fig. 6. Thus, a total of 10 hidden layers have been considered for prediction of the glucose level values.

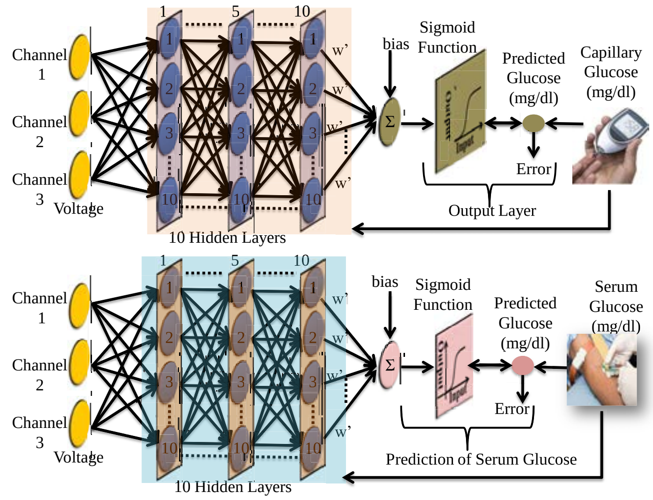


Fig. 5. The Deep Neural Network (DNN) model used for calibration.

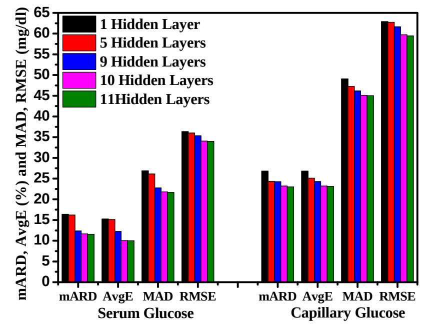


Fig. 6. Error analysis of DNN models using different hidden layers.

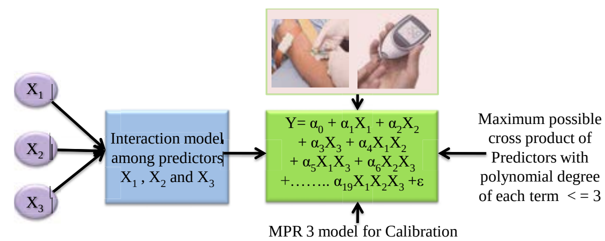


Fig. 7. The Multiple polynomial regression of degree 3 (MPR 3) model representation for calibration.

B. Proposed Method 2: Multiple Polynomial Regression (MPR) model of Glucose Concentration

Multiple polynomial regression of degree 3 (MPR 3) is also attempted for capillary and serum glucose prediction. The regression model of cubic kernel is applied for the predicted glucose values of iGLU 2.0. The multiple polynomial regression model (MPR 3) kernel is calibrated as:

$$
\begin{aligned}
y = {} & a_1x_1^3 + a_2x_2^3 + a_3x_3^3 + a_4x_1^2x_2 + a_5x_1^2x_3 + a_6x_1x_2^2 \\
& + a_7x_1x_3^2 + a_8x_2^2x_3 + a_9x_2x_3^2 + a_{10}x_1^2 + a_{11}x_2^2 + a_{12}x_3^2 \\
& + a_{13}x_1x_2x_3 + a_{14}x_1x_2 + a_{15}x_1x_3 + a_{16}x_2x_3 + a_{17}x_1 \\
& + a_{18}x_2 + a_{19}x_3 + \epsilon. \quad (1)
\end{aligned}
$$

In the above expression, the output voltage values from three channel are defined as x_1, x_2 and x_3 independent variables (predictors), whereas the predicted value of the glucose (mg/dl) is the dependent on variable y. The overall representation of MPR3 model is shown in Fig. 7. a_1-a_{19} are regression coefficients and ϵ is a residual error. These values are dependent on the predictors and the corresponding response of calibrated model. Proposed MPR3 is multivariate regression model and total 19 customized interacted variables based kernel is observed as optimized model.

The correlation plots between predicted and reference glucose concentration are represented in Fig. 8(a) - Fig. 8(h). The error analysis of the proposed model is reported in Table II.

Proposed MPR 3 model represents better results of calibration and validation compared to DNN based model. The serum glucose is found more accurate compared to capillary glucose using MPR 3.

VI. Design of the Proposed Novel Glucometer for Serum Glucose Monitoring - The iGLU 2.0

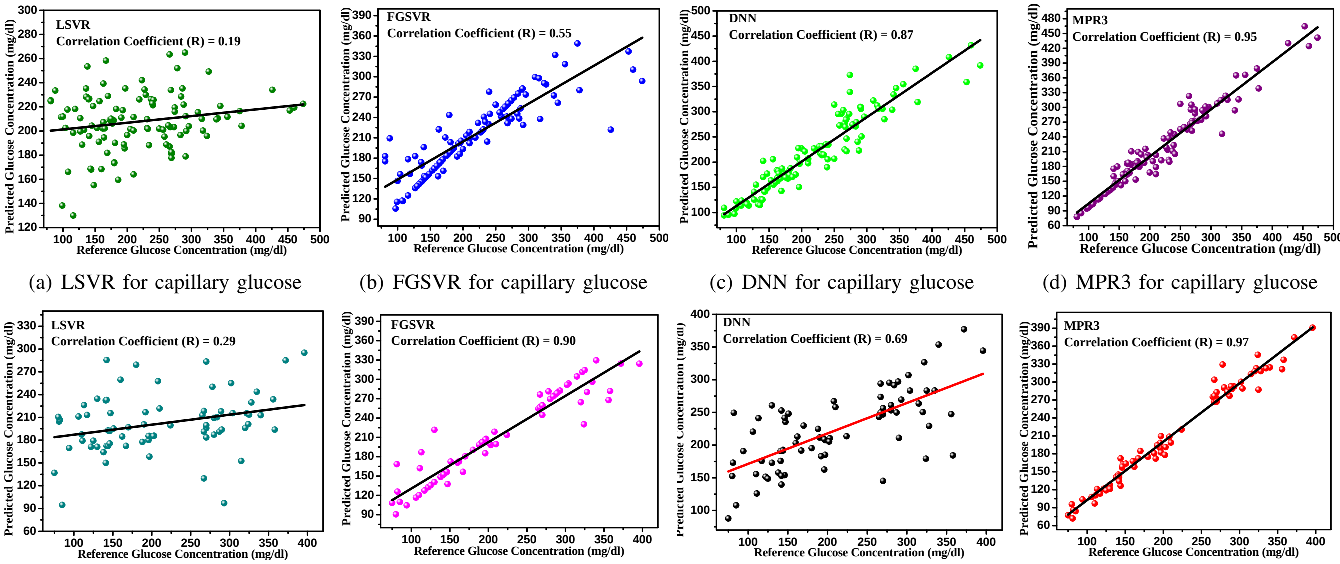
The proposed glucometer uses the concept of short wave NIR spectroscopy with two different wavelengths (940 and 1300 nm) and is implemented with three channels. Each channel has particular wavelength emitter and detector to detect the glucose.

A. The Proposed Approach for Data Acquisition

The data is acquired and is also logged subsequently using 16 bit ADC with sample rate of 128 samples/sec. The logged data is calibrated and is further validated through an optimized model of existing regression techniques for precise measurement. Independent samples are collected from the age group

TABLE II
Statistical Analysis of Calibration of Different Models

Regression Model	mARD %	AvgE %	MAD mg/dl	RMSE mg/dl
Linear SVR (Capillary)	34.40	31.27	65.64	83.50
Serum	39.24	36.21	70.59	83.21
Cubic SVR (Capillary)	31.85	27.32	59.42	79.66
Serum	26.69	32.55	51.92	73.32
Quadratic SVR (Capillary)	33.43	29.73	63.59	81.38
Serum	33.42	10.86	61.35	83.47
Medium Gaussian SVR (Capillary)	31.36	26.82	58.43	77.83
Serum	26.50	24.66	47.75	66.01
Coarse Gaussian SVR (Capillary)	33.71	30.74	64.58	82.10
Serum	40.09	34.75	70.37	81.05
Fine Gaussian SVR (Capillary)	14.31	12.49	27.36	45.06
Serum	12.31	10.45	20.96	31.09
DNN (Capillary)	29.06	22.14	46.47	62.51
Serum	9.11	8.95	19.47	27.95
MPR3 (Capillary)	6.07	6.09	13.28	19.71
Serum	4.86	4.88	9.42	13.57



(a) LSVR for capillary glucose (b) FGSVR for capillary glucose (c) DNN for capillary glucose (d) MPR3 for capillary glucose

(e) LSVR for serum glucose (f) FGSVR for serum glucose (g) DNN for serum glucose (h) MPR3 for serum glucose

Fig. 8. Correlation plot of predicted and referenced blood glucose concentration during calibration of regression models.

of 24-50 which would help to test and to validate our iGLU 2.0. A 2 layer PCB is designed and system is developed to embed NIR LEDs and detectors.

The circuit is implemented to design the optical detection mechanism [29]. The components of the circuit such as, analog-to-digital converter (ADC), emitters and detectors are integrated with optimized biasing with 5 V DC supply. Passive components have been chosen to provide better efficiency of NIR LEDs and detectors. All NIR LEDs and detectors are connected in photoconductive mode. All detectors have specifications of daylight blocking filters. The ADC is used to transfer the data over three channels in serial manner in decimal form. A microcontroller is used to control the ADC.

B. The Proposed System of the Glucometer

The paper covers the absorptions and reflection based optical detections to detect glucose molecule with the change in light intensity. The output voltages of the detectors are dependent on the received light intensity. The voltage output is logged by placing the fingertip (or earlobe) in between emitter and detector of NIR LEDs. The coherent averaging is performed at output voltage samples for reducing the measurement error. The averaging of overall 1024 samples is considered for the purpose of the calibration and validation over the period of the time span of 8 seconds. The block level diagram of proposed iGLU 2.0 is represented in Fig. 9. The serum glucose is measured at the laboratory, whereas the capillary glucose has been measured using invasive glucometer SD check as gold standard for validation purpose [37]. The values from serum and capillary glucose are considered as the reference glucose values (mg/dl). The responses of detectors (in milivolts) are collected from all three channels at the same time. The values from the ADC are corresponding to serum and capillary glucose values.

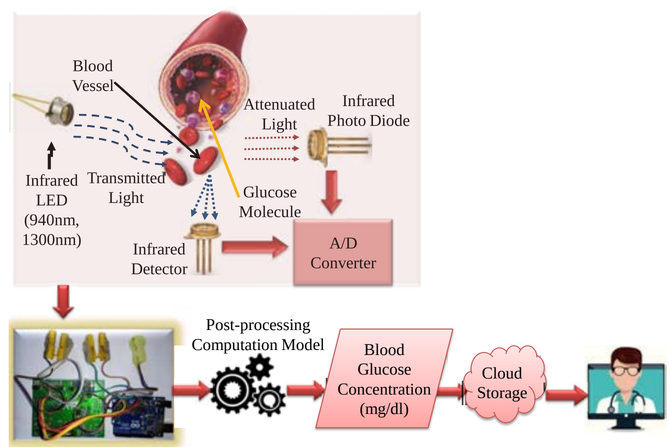


Fig. 9. Schematic representation of proposed device (iGLU 2.0).

VII. Validation of the Proposed Device iGLU 2.0

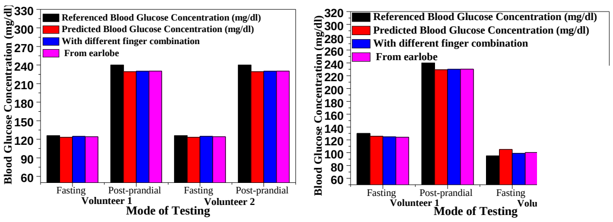
A. Testing and Error Analysis

There are total 50 different samples of capillary glucose and 37 samples are considered of serum glucose from prediabetic, diabetic and healthy subjects to validate the iGLU 2.0 device. Total 46 samples from 20 females and 26 males are tested for the validation purpose by following medical protocols. The samples are collected in fasting, post-prandial and random modes for the validation and testing. The baseline characteristics are already defined in Table I and the error analysis is shown in Table III.

Two volunteers are chosen to verify the device stability with multiple measurements of capilary and serum glucose through iGLU 2.0. The experiment is performed at fasting and post-prandial mode and results are shown in Fig. 10.

TABLE III
STATISTICAL ANALYSIS OF VALIDATION OF PROPOSED MOI

Regression Model	mARD %	AvgE %	MAD mg/dl	RMSE mg/dl
DNN (Capillary)	23.19	22.14	45.07	59.74
Serum	11.67	10.02	21.81	34.05
MPR3 (Capillary)	7.74	7.70	16.08	22.46
Serum	5.009	4.97	9.74	12.98



(a) Samples of capillary glucose (b) Samples of serum g

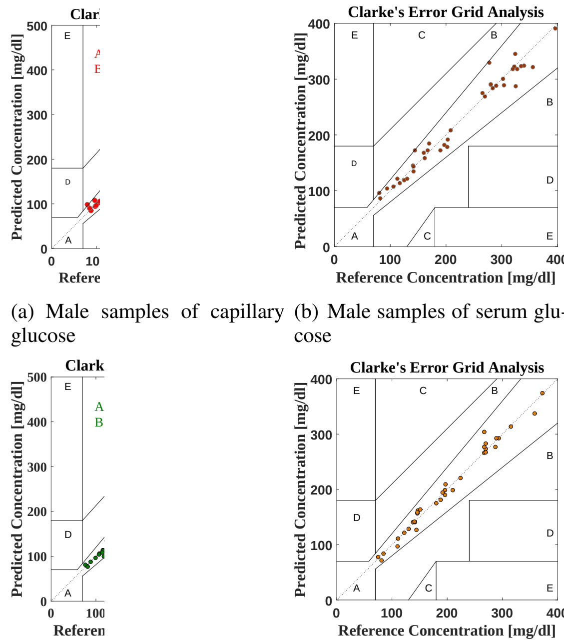
Fig. 10. Predicted and reference blood glucose concentration fc of iGLU 2.0 on 2 volunteers.

B. Clarke Error Grid (CEG) Analysis

This error is analysed for predicted blood glucose to validate the precision level of iGLU 2.0 [38]. The Clarke analysis is useful to explore the variation between referenced and predicted glucose concentration with different zones. The wise samples are arranged to observe the accuracy 2.0 with testing and validation which are represented i and 12, respectively. The results confirm the usage o iGLU 2.0 for clinical purposes. The proposed device compared with previous non invasive approaches in T in which "NA" indicates value is missing or not report existing works. The proposed iGLU 2.0 device has linearity (97%) and high measurement range (80-42 mg/dl) in comparison with other NIR measurement techniques. The proposed device provides very good results due to unique combination of absorption and reflectance spectros two specific wavelengths (940 nm and 1300 nm). A to Table V, the proposed iGLU 2.0 is more ac comparison to other glucose non-invasive monitoring The results of iGLU 2.0 is the best because it is the c which considers the serum glucose measurement. It observed that all samples of serum glucose from devices exist in zone A and the samples of all other methods are of capillary glucose which exist in zone A and zone B. The serum blood glucose measurement always has better precision as compared to capillary measurement. The proposed iGLU 2.0 device is first ever attempt of the serum glucose measurement in the era of non-invasive glucometer. Hence, the accuracy of glucometer is the highest among all previous non-invasive glucose measurement.

VIII. CONCLUSIONS

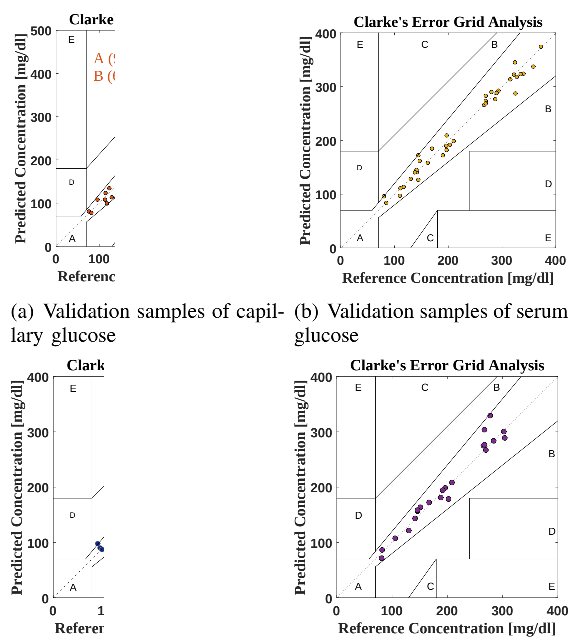
This work presented a IoMT enabled wearable consumer device called iGLU 2.0 for continuous glucose monitoring for diabetic patients. It is based on the principle of optical detection and the efficient regression model is developed to measure the accurate serum glucose measurement. The device is validated on pre-diabetic, diabetic and healthy patients from persons aged 17-80 using real healthcare data. It has been observed that $AvgE$ and $mARD$ represent better results of calibration and validation for serum glucose compared to capillary glucose. The estimated samples of serum glucose values are observed at 100% in zone A. The propose glucometer is



(a) Male samples of capillary glucose (b) Male samples of serum glucose

(c) Female samples of capillary glucose (d) Female samples of serum glucose samples

Fig. 11. CEG analysis of predicted capillary and serum glucose concentration of male and female subjects for iGLU 2.0 device.



(a) Validation samples of capillary glucose (b) Validation samples of serum glucose

(c) Testing samples of capillary glucose (d) Testing samples of serum glucose samples

Fig. 12. CEG analysis of predicted blood glucose concentration for validation and testing of iGLU 2.0 device.

TABLE IV
APPROACHES COMPARISON WITH NON-INVASIVE WORKS

Research Works	Spectroscopy Technique	Spectra	Specific Wavelength	Measurement Range	Linearity
Singh, et al. [23]	Optical	-	-	32-516 mg/dl	80
Song, et al. [25]	Impedance and Reflectance	NIR	850-1300 nm	80-180 mg/dl	NA
Pai, et al. [39]	Photoacoustic	NIR	905 nm	upto 500 mg/dl	NA
Dai, et al. [24]	Bioimpedance	-	-	-	NA
Beach, et al. [21]	Biosensing	-	-	-	NA
Ali, et al. [34]	Transmittance and Refraction	NIR	650 nm	upto 450 mg/dl	NA
Haxha, et al. [35]	Transmission	NIR	940 nm	70-120 mg/dl	96
Proposed Work (iGLU 2.0)	**Absorption and Reflectance**	NIR	**940 and 1300 nm**	**80-420 mg/dl**	**97**

TABLE V
STATISTICAL AND PARAMETRICAL COMPARISON WITH NON-INVASIVE WORKS

Research Works	R value	mARD (%)	AvgE (%)	MAD (mg/dl)	RMSE (mg/dl)	Samples (100%)	Used model	Measurement sample	Device cost
Singh, et al. [23]	0.80	-	-	-	-	A&B	Human	Saliva	Cheaper
Song, et al. [25]	-	8.3	19	-	-	A&B	Human	Blood	Cheaper
Pai, et al. [39]	-	7.01	-	5.23	7.64	A&B	in-vitro	Blood	Costly
Dai, et al. [24]	-	5.99	5.58	-	-	-	in-vivo	Blood	Cheaper
Beach, et al. [21]	-	-	7.33	-	-	-	in-vitro	Solution	-
Ali, et al. [34]	-	8.0	-	-	-	A&B	Human	Blood	Cheaper
Haxha, et al. [35]	0.96	-	-	-	33.49	A&B	Human	Blood	Cheaper
Jain, et al. [4]	0.90	5.20	5.14	5.82	7.5	A&B	Human	Blood	Cheaper
Jain, et al. (iGLU) [29]	0.95	6.65	7.30	12.67	21.95	A&B	Human	Blood	Cheaper
Proposed Work (iGLU 2.0)	**0.97**	**4.86**	**4.88**	**9.42**	**13.57**	**Zone A**	**Human**	**Blood**	**Cheaper**

precise and cost-effective solution and is useful to measure the blood glucose in the range of 80-420 mg/dl. Proposed iGLU 2.0 has a great potential to provide self care monitoring solution for smart healthcare.

Our future research is towards the development machine learning models for required insulin secretion for automatic insulin delivery of seriously diabetic patients in IoMT framework activated by iGLU 2.0. We will also focus on determining the impact of continuous glucose-level measurement with iGLU on other critical health conditions, such as blood pressure, heart stroke, and epileptic seizure. In the future, we intend to work on the security and privacy solutions of the IoMT enabled iGLU device as well as security and privacy of personal health data.

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REFERENCES

[1] H. Zhu, C. K. Wu, C. H. Koo, Y. T. Tsang, Y. Liu, H. R. Chi, and K. Tsang, "Smart healthcare in the era of Internet-of-Things," *IEEE Consum. Electron. Mag.*, vol. 8, no. 5, pp. 26–30, Sep 2019.

[2] M. Ghamari, B. Janko, R. Sherratt, W. Harwin, R. Piechockic, and C. Soltanpur, "A survey on wireless body area networks for eHealthcare systems in residential environments," *MDPI Sensors*, vol. 16, no. 6, p. 831, Jun 2016.

[3] 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, July 2016.

[4] P. Jain, S. Pancholi, and A. M. Joshi, "An IoMT based non-invasive precise blood glucose measurement system," in *Proc. IEEE Int. Conf. Smart Elect. Sys.*, 2019, pp. 111–116.

[5] C. Solis-Herrera, C. Triplitt, C. Reasner, R. A. DeFronzo, and E. Cersosimo, "Classification of diabetes mellitus," 2019, Last Accessed on 02 Apr 2020. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK279119/

[6] I. D. Federation, "IDF diabetes atlas - diabetes is rising worldwide... and is set to rise even further," 2019, last Accessed on 21 March 2020. [Online]. Available: https://diabetesatlas.org/en/sections/worldwide-toll-of-diabetes.html

[7] H. Yin, B. Mukadam, X. Dai, and N. Jha, "DiabDeep: pervasive diabetes diagnosis based on wearable medical sensors and efficient neural networks," *IEEE Trans. Emerg. Topics Comput.*, pp. 1–1, 2019.

[8] H. Thapliyal, V. Khalus, and C. Labrado, "Stress detection and management: a survey of wearable smart health devices," *IEEE Consum. Electron. Mag.*, vol. 6, no. 4, pp. 64–69, Oct 2017.

[9] S. H. Chae and M. C. Kang and J. Y. Sun and B. S. Kim and S. J. Ko, "Collision detection method using image segmentation for the visually impaired," *IEEE Trans. Consum. Electron.*, vol. 63, no. 4, pp. 392–400, Nov 2017.

[10] C. W. Lee, P. Chondro, S. J. Ruan, O. Christen, and E. Naroska, "Improving mobility for the visually impaired: a wearable indoor positioning system based on visual markers," *IEEE Consum. Electron. Mag.*, vol. 7, no. 3, pp. 12–20, May 2018.

[11] J. Wang, Z. Zhang, B. Li, S. Lee, and R. S. Sherratt, "An enhanced fall detection system for elderly person monitoring using consumer home networks," *IEEE Trans. Consum. Electron.*, vol. 60, no. 1, pp. 23–29, 2014.

[12] M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. P. Zaveri, "Neuro-Detect: a machine learning-based fast and accurate seizure detection system in the IoMT," *IEEE Trans. Consum. Electron.*, vol. 65, no. 3, pp. 359–368, August 2019.

[13] S. Raj and K. C. Ray, "A personalized point-of-care platform for real-time ECG monitoring," *IEEE Trans. Consum. Electron.*, vol. 64, no. 4, pp. 452–460, Nov 2018.

[14] S. Lee, P. Huang, M. Liang, J. Hong, and J. Chen, "Development of an arrhythmia monitoring system and human study," *IEEE Trans. Consum. Electron.*, vol. 64, no. 4, pp. 442–451, Nov 2018.

[15] N. Dey and A. S. Ashour and F. Shi and S. J. Fong and R. S. Sherratt, "Developing residential wireless sensor networks for ECG healthcare monitoring," *IEEE Trans. Consum. Electron.*, vol. 63, no. 4, pp. 442–449, Nov 2017.

[16] D. W. Ryoo and C. S. Bae and J. W. Lee, "The wearable wrist-type gadget for healthcare based on physiological signals," in *Proc. IEEE Int. Conf. Consum. Electron.*, 2008.

[17] P. Li, Y. Wang, Y. Tian, T.-S. Zhou, and J.-S. Li, "An automatic user-adapted physical activity classification method using smartphones," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 3, pp. 706–714, 2016.

[18] S. Twetman, "Prevention of dental caries as a non-communicable disease," *European J. Oral Sc.*, vol. 126, pp. 19–25, 2018.

[19] A. Fotopoulou and K. ORiordan, "Training to self-care: fitness tracking, biopedagogy and the healthy consumer," *Health Socio. Rev.*, vol. 26, no. 1, pp. 54–68, 2017.

[20] P. Jain, A. M. Joshi, and S. P. Mohanty, "iGLU 1.0: An accurate non-invasive near-infrared dual short wavelengths spectroscopy based glucometer for smart healthcare," *arXiv preprint arXiv:1911.04471*, 2019.

[21] R. D. Beach, R. W. Conlan, M. C. Godwin, and F. Moussy, "Towards a miniature implantable in vivo telemetry monitoring system dynamically configurable as a potentiostat or galvanostat for two- and three-electrode biosensors," *IEEE Trans. Instrum. Meas.*, vol. 54, no. 1, pp. 61–72, Feb 2005.

[22] M. S. Prasad, R. Chen, Y. Li, D. Rekha, D. Li, H. Ni, and N. Y. Sreedhar, "Polypyrrole supported with copper nanoparticles modified alkali anodized steel electrode for probing of glucose in real samples," *IEEE Sensors J.*, vol. 18, no. 13, pp. 5203–5212, July 2018.

[23] A. K. Singh and S. K. Jha, "Non-invasive, optical biosensor for self-monitoring of glucose using saliva," *IEEE Sensors J.*, vol. 19, no. 18, pp. 8332–8339, Sep. 2019.

[24] T. Dai and A. Adler, "In vivo blood characterization from bioimpedance spectroscopy of blood pooling," *IEEE Trans. Instrum. Meas.*, vol. 58, no. 11, p. 3831, 2009.

[25] 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, April 2015.

[26] L. R. De Pretto, T. M. Yoshimura, M. S. Ribeiro, and A. Z. de Freitas, "Optical coherence tomography for blood glucose monitoring in vitro through spatial and temporal approaches," *J. Biomed. Opt.*, vol. 21, no. 8, p. 086007, 2016.

[27] 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. Ther.*, vol. 14, no. 9, pp. 819–827, 2012.

[28] W.-C. Shih, K. L. Bechtel, and M. V. Rebec, "Noninvasive glucose sensing by transcutaneous raman spectroscopy," *J. Biomed. Opt.*, vol. 20, no. 5, p. 051036, 2015.

[29] P. Jain, A. M. Joshi, and S. P. Mohanty, "iGLU: an intelligent device for accurate non-invasive blood glucose-level monitoring in smart healthcare," *IEEE Consum. Electron. Mag.*, vol. 9, no. 1, Jan 2020, pp. 35-42.

[30] P. Jain, R. Maddila, and A. M. Joshi, "A precise non-invasive blood glucose measurement system using NIR spectroscopy and Hubers regression model," *Opt Quantum Electron*, vol. 51, no. 2, p. 51, 2019.

[31] 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.

[32] 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.

[33] S. Sharma, M. Goodarzi, L. Wynants, H. Ramon, and W. Saeys, "Efficient use of pure component and interferent spectra in multivariate calibration," *Anal. Chim. Acta*, vol. 778, pp. 15–23, 2013.

[34] H. Ali, F. Bensaali, and F. Jaber, "Novel approach to non-invasive blood glucose monitoring based on transmittance and refraction of visible laser light," *IEEE Access*, vol. 5, pp. 9163–9174, 2017.

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

[36] 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.

[37] J. A. Seo, N. H. Kim, S. G. Yun, C. H. Cho, J. H. Yang, C. S. Lim, Y. K. Kim, and K. N. Lee, "Clinical evaluation of sd check gold as point-of-care glucose meter," *J Lab Med Qual Assur*, vol. 31, no. 2, p. 261, 2009.

[38] W. L. Clarke, "The original Clarke error grid analysis (EGA)," *Diabetes Technol. Ther.*, vol. 7, no. 5, pp. 776–779, 2005.

[39] P. P. Pai, A. De, and S. Banerjee, "Accuracy enhancement for non-invasive glucose estimation using dual-wavelength photoacoustic measurements and kernel-based calibration," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 1, pp. 126–136, 2018.

[40] P. Jain, A. M. Joshi, N. Agrawal, and S. P. Mohanty, "iGLU 2.0: a new non-invasive, accurate serum glucometer for smart healthcare," *arXiv Electrical Engineering and Systems Science*, vol. abs/2001.09182, 2020. [Online]. Available: http://arxiv.org/abs/2001.09182

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