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iGLU 4.0: Intelligent Non-Invasive Glucose Measurement and Its Control with Physiological Parameters

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Abstract The conventional glucose measurement method, such as pricking blood from the body, is prevalent, bringing pain and trauma. Invasive measurement methods sometimes raise the risk of blood infection in the patient. Several physiological parameters, such as body temperature and systolic blood pressure (SBP) are responsible for blood glucose level fluctuations. Moreover, diabetes for a long duration usually becomes a critical issue. The patients are required to measure blood glucose recurrently and need to take action for the control of blood glucose. Therefore, it is required to develop a non-invasive glucose balancing paradigm, which measures blood glucose without pricking blood along with physiological parameters measurement and decision model. The proposed paradigm helps doctors to connect with patients at a remote location. Hence, an intelligent, non-invasive system using a Near Infra Red is proposed, including physiological parameters to predict the precise glucose value. The decision model includes all parameters (glucose, Blood pressure and body temperature), food intake and insulin levels. This would help the doctor to decide on further medication and control mechanisms. The proposed system demonstrated an accurate model with mARD 12.50% and AvgE 12.10% using the DNN model. The coefficient of determination R^2 is 0.97.

Keywords Healthcare Cyber-Physical System (H-CPS), Non-invasive Glucose Monitoring, Smart Healthcare, Physiological Parameters, Near Infrared (NIR)

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1 Introduction

Diabetes is one of the world's most challenging diseases for human health. The WHO also declares that 79%-82% of diabetic deaths occur in developing countries [1]. Nowadays, balancing blood glucose has become one of the global challenges for human life. People prefer a balanced routine and prescribed diet plan to keep blood glucose normal. Due to this, a person will be able to keep a healthy routine for a quality life. The normal blood glucose level advantages are represented in Fig.1. When the person has an issue balancing the body's glucose level, it refers to Glycemic imbalance [2,3]. The imbalance in the context of hyperglycemia is the prime factor in increasing the probability of being a diabetic patient. An unbalanced diet is one of the main factors for the occurrence of diabetes Mellitus [4]. Hence, timely diagnosis and better treatment of diabetes are the focusing points of research on recent healthcare trends. Therefore, it is required to analyze the factors which are responsible for fluctuating blood glucose. Various parameters contribute towards unexpected variations of glucose levels in the human body. Most commonly, these four parameters have been considered for variation in blood glucose levels, which is represented in Fig. 2.

Many cases have been observed for blood glucose fluctuation because of changes in physiological parameters. The other body parameters are also responsible for fluctuating blood glucose levels in the case of diabetic patients. The physiological parameters and blood glucose level are considered for precise blood glucose measurement.

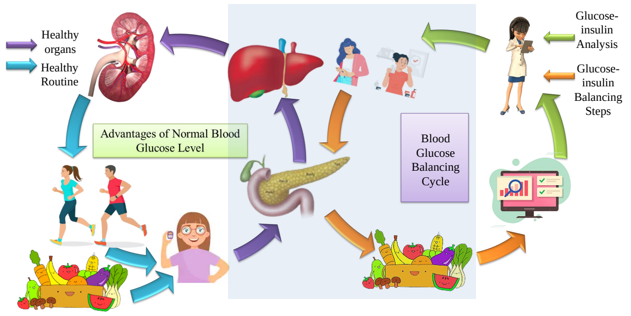


Fig. 1 Advantages of normal blood glucose level and balancing cycle

Continuous fever in the body or hypertension may be the factors for the sudden change in blood glucose level. Hence, various physiological parameters and other factors are required to compute along with blood glucose level values for training of the device. With the development of technology, patients can control their blood glucose more precisely. By using such type of paradigm, the healthcare provider would be able to provide proper diagnosis treatment. Such a paradigm provides transparency in the current situation and precise diagnosis. Using such technology can overcome some more constraints in the era of blood glucose management. It has been observed that the type of insulin doses are specified in terms of short and long-acting for different cases. As per the advancement in healthcare technology, it is required to provide the necessary details of the patients to the medical consultant at remote locations. The overall paper has been arranged in the given sequence. Prior research work is reported in Section 2. The significance of physiological parameters is demonstrated along with novel contribution in Section 3. The proposed system is described with the process of glucose detection in Section 4. Section 5 elaborates on machine learning models for system calibration and validation. The experimental analysis has been done in Section 6.

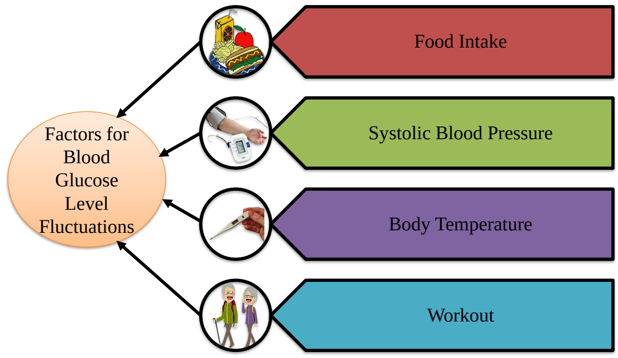


Fig. 2 Representation of factors affecting blood glucose level

2 Prior Related Research Work

Various glucose measurement products based on electrochemical mechanisms have been proposed in the literature to measure blood glucose accurately. The minimally invasive approach-based implantable biosensors have been proposed earlier for continuous measurements with glucose oxidase generation. These are implanted beneath the skin for continuous measurement. The photometric technique was also attempted to detect glucose molecules in blood drops.

The minimally invasive approaches were used to develop frequent glucose monitoring sensors [5]. The wearable sensors are implanted to analyze the results for continuous glucose monitoring from the membrane, which contains the immobilized glucose oxidase. Glucose monitoring biosensors are configured with auxiliary frameworks to provide the environment of continuous glucose monitoring through the implantation mechanism. These minimally invasive methods have been experimented on intensive care required diabetic patients. The wearable sensors-based microsystem was explored for continuous glucose monitoring to make a portable solution for frequent monitoring. Likewise, there was a solution for continuous monitoring using a biosensor with the help of a transponder chip [6]. The response obtained from the transponder chip was processed for the calibration of the semi-invasive technique of the Dexcom sensor. Diabetes balancing has been explored through sensors with the system nominated as an artificial pancreas system. The minimally invasive techniques-based designs are identified with some limitations, such as precision in glucose values, and will have a shorter life span for monitoring [7].

Optical methods-based blood glucose measurement systems have been proposed to detect blood glucose without pricking the blood from the fingertip. Various bio-potential-based techniques have been explored to detect the blood glucose of human beings [8]. Using these techniques, the detection of glucose molecules through skin resistance, dielectric constant and capacitance has been proposed [9]. Glucowise is a non-invasive blood glucose monitoring device currently being tested for clinical purposes [10]. This device explored the impedance spectroscopy technique. The change in the blood glucose concentration depends upon the impedance variation. However, the change in object position may be referred to as blood glucose variation. Hence, the device will not be precise for all patients. Much work has been proposed for glucose detection through human tears, saliva, and sweat. The continuous wave multi-wavelength photo-acoustic technique is also discussed for glucose detection [11]. Pai et.al. proposed the pulse width modulated photo-acoustic spectroscopy technique for glucose detection [12]. However, there is not yet a commercially viable solution for medication purposes. After consideration of further advancement and benefits of NIR spectroscopy, an initial prototype setup has been calibrated and validated for precise blood glucose measurement. This prior work was a motivation to develop an edge computing intelligent device for the same application. Then, iGLU, an intelligent blood glucose measurement system, has been developed for smart healthcare [13]. This prior intelligent system could measure capillary blood glucose with almost 98% accuracy. Further, iGLU 2.0 has been developed with the same methodology to measure serum glucose measurement [14]. That proposed system reported massive performance parameters in terms of predicting genuine blood glucose levels, as serum glucose is usually considered the exact level for proper medication [15]. Following this work, iGLU 1.1 is proposed with a glucose-insulin control virtual paradigm, which reported analytical studies on various standard subjects of diabetic patients [16]. iGLU 3.0 was developed to provide a specific device and data security feature. An optimized secure iGLU is formed using a standard encrypted algorithm [17]. Many non-invasive systems are proposed to provide precise glucose measurement systems. Most of them are suitable for measuring blood glucose measurement using some spectroscopy techniques [18]. However, it is required to predict the other factors which are directly and indirectly responsible for blood glucose fluctuation. The most important factors, such as body temperature and blood pressure, are highlighted in this paper to justify blood glucose fluctuation.

Based on literature work and spectrum analysis, it is also analyzed that glucose detection will be more accurate involving optical detection method [20]. Therefore, the current work uses 940 nm and 1300 nm wavelength-specific light for glucose detection to predict physiological parameters.

The body temperature and systolic blood pressure are key parameters which may be related to the blood glucose concentration. If body temperature rises, artery walls dilate, enhancing insulin consumption. This may result in low blood glucose levels. Besides this, consistently high blood glucose may result in the hardening of artery walls. This is one of the causes of high blood pressure. Table 1 demonstrated the prior work done in a non-invasive paradigm and specific features advancement in current work.

3 Proposed Methodology for Glucose Measurement and Novel Contribution

For diabetes care, it is necessary to design a blood glucose monitoring system which could be available in rural and urban areas with minimum cost and ease of use [19]. Presently, most successive and commercially available blood glucose measuring devices are invasive. These devices are accurate and recommended for blood glucose tests for health care. Highly accurate conventional laboratory tests are preferred for diabetes patients [12]. These types of blood glucose measurements are not better for frequent monitoring. For diabetic patients, measuring multiple times a day is necessary, which causes irritation and trauma. Meanwhile, consumable lancets and strips contaminate the body's blood. To avoid these problems, the non-invasive glucose monitoring paradigm has been explored in previous research work [20]. Sometimes, it has been observed that the blood glucose level fluctuates concerning the imbalance of physiological parameters. Hence, the precise estimation of body glucose is only possible when physiological parameters can be predicted simultaneously. Then, a precise diagnosis would be possible. Prior non-invasive systems have been designed without consideration of physiological parameters and diabetic history of patients.

Therefore, the consultant won't be able to provide a precise treatment in specific cases, such as patients with fever or hypertension and a corresponding history of medicine intake. To overcome these issues, a novel non-invasive system with a history of medicine intake is required to propose integrating physiological parameters such as SBP and body temperature for real-time validation. These two parameters are responsible for blood glucose variation, shown in Fig.2. The proposed system is calibrated according to fasting, postprandial, and random testing modes of blood glucose readings. Then, the system is tested by comparing non-invasive and corresponding invasive predicted blood glucose values.

Table 1 Non-invasive Works in Technology and Features Perspective

Works	Method	Technology	Cost	Reliability	Functional Specification
Song,et al. [19]	IMPS +NIRS	Sensing+ Measurement	Mod.	Mod.	Glucose Measurement
Pai,et al. [12]	Photo -acoustic	Sensing+ Measurement	High	High	Glucose Measurement
Jain,et al. [20]	mNIRS	Sensing	Low	Mod.	Glucose Measurement
Jain,et al. [21]	mNIRS	Sensing+ Trained Model	Low	High	Glucose Measurement
Joshi,et al. [22]	mNIRS	Sensing+ Trained Model	Low	High	Serum Glucose Measurement
Joshi, et al. [17]	mNIRS+ Data Security	Sensing+ Trained Model	Low	High	BG,Insulin Measurement
Jain, et al.[16]	Computing Model	Trained Model	Mod.	Mod.	Glucose Insulin Model
Murad, et al.[23]	mNIRS	Simulation	-	-	Glucose Detection
Kirubakaran, et al.[24]	Microwave	Sensing	High	Mod.	Glucose Measurement
Mohammadi, et al.[25]	Microwave Resonator	Sensing	High	Mod.	Glucose Detection
(iGLU 4.0)	**mNIRS+ Model**	**Sensing+ Measurement**	**Mod.**	**High**	**Glucose Balancing Paradigm**

3.1 Novel Contribution of Proposed Work

The proposed blood glucose balancing paradigm is non-invasive and measures precise blood glucose considering various physiological parameters. It also reduces the probability of having blood-related diseases as the measurement is possible without pricking the blood. The proposed methodology adopts an optical approach and uses the optimized prediction model for estimation. The physiological parameters have helped to have the precise and rapid diagnosis. The proposed system has no need for prior setup for measurement. The system can measure any person's blood glucose at any time. The system will be portable after packaging to use everywhere. The system is an easy-to-use, fast-operated, low-cost solution for smart healthcare. Proposed iGLU 4.0 is used to provide the facility of continuous monitoring and other vital parameter estimation, which are responsible for fluctuation. The proposed intelligent device stores values in the cloud to consultant the healthcare provider for reliable patient treatment. The feature advancement is demonstrated in Fig. 3. The **novel contribution in proposed work** are the following:

1. An accurate, non-invasive glucometer is developed to predict te glucose value with other physiological parameters. The continuous monitoring of parameters is logged and accessible by users using the IoMT framework.
2. The optimized prediction model has been calibrated, validated and tested using a suitable data set for precise diagnosis of blood glucose fluctuations.
3. The blood glucose values are stored in the cloud for telemedicine purposes and analyzed further to provide better treatment.

4 iGLU 4.0: Proposed Non-invasive Glucose Measurement with Physiological Parameters

The proposed iGLU 4.0 device is based on optical detection methods where light is incident on the fingertip. The prediction of blood glucose has been made by placing the fingertip between the gap of the transmitter and receiver sensor. The voltage variation would be observed as per glucose concentration inside the blood. These voltage values are processed along with systolic blood pressure and body temperature to estimate predicted blood glucose through the data acquisition module. The proposed system design of non-invasive glucose detection consists of optimized three-channel multi-wave reflection and absorption spectroscopy [21]. The pictorial view of process flow for the proposed glucometer is represented in Fig. 4. The non-invasive glucose balanc-

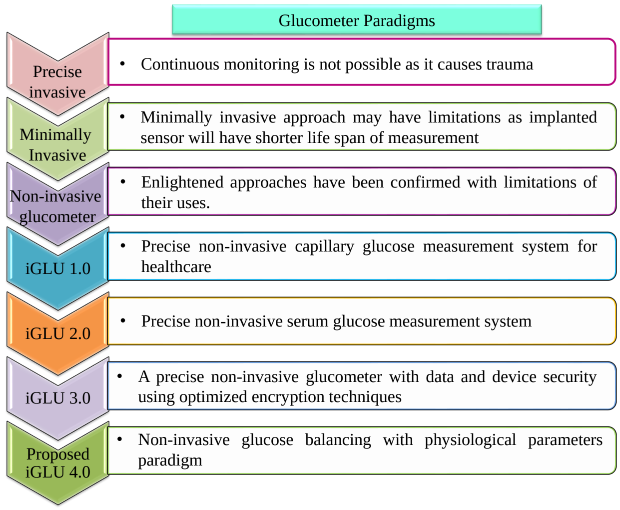


Fig. 3 Representation of glucose measurement paradigm with challenges

ing paradigm consists of two modules indirectly. The first module senses blood glucose with channel voltage and physiological parameter values. The glucose level is predicted using an optimized DNN model. The predicted values in different time durations have been considered to obtain other body glucose parameters. The sensing part has been validated for accuracy perspective from the conventional measurement process.

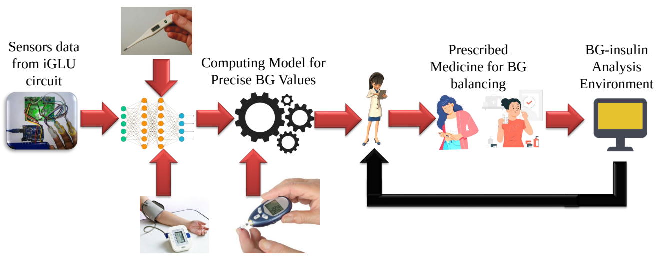


Fig. 4 The pictorial view of process flow for proposed balancing environment.

The estimated glucose values are considered to analyze the data of scheduled food intake and insulin secretion in the body. Based on the decision data, a medical consultant could diagnose the actual blood glucose values and the cause of fluctuation if it occurs. According to Fig. 5, the precise blood glucose values are obtained using a trained model after estimating physiological parameters. The proposed system balances the glucose values after analyzing the data of all other parameters. Hence, the proposed paradigm consists of two different mathematical models. The first model has been trained for non-invasive glucose prediction. The other decision model is to obtain the insulin level so that blood glucose level can be balanced based on food intake, physical activity and prescribed medicine plan. The main significance of the proposed system is that the medical consultant would have prior information about patients and their related things. The medical consultant needs to provide treatment based on the proposed system's prior information. This feature will reduce enough effort and time consumption to justify the cause of fluctuation, and further treatment will be provided earlier.

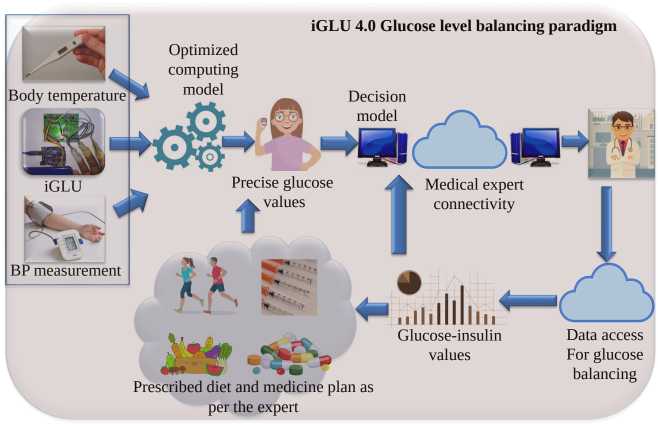


Fig. 5 Proposed non-invasive glucose measurement and balancing paradigm

5 Proposed Machine Learning Model For Glucose Estimation with Validation

The post-processing computation model is used to interpret the response of the proposed system in estimated glucose value for monitoring. It is necessary to analyze the post-processing model for precise output estimation [26]. The characteristics of collected data are represented in Table 2. The age range of the subject has been taken from 17-65 years as data is required to be taken from all ages of people. According to the characteristics of the data in Table 2, the male data has been taken from 22-65 and female data has been taken from 17-43 as per the availability of samples for clinical tests. The high variability data range is required to train and validate the device from a precision point of view. The variability in physiological parameters is represented in Fig. 11, where body temperatures and blood pressures are converged in the plot. The body temperature may differ and can't be concerning the range of age. Similarly, the SBP range is also not dependent upon the range of the age. Hence, the data has been categorized

Table 2 Charactestics of Collected Data

Samples Basic Characteristics	**Samples with Glucose Values**	**Samples with Physiological Parameters**
Gender Male:- **62** Female:- **54**	**Hyperglycemia** Male:- **40** Female:- **30**	**SBP** All samples with different SBP
Age (Years) Male:- **22-65** Female:- **17-43**	**Hypoglycemia** Male:- **08** Female:- **10** **Healthy** Male:- **14** Female:- **14**	**Body Temperature** All samples with different body temperature

as per the gender and glucose values range. The diagram of the processing steps of the proposed glucose measurement system is given in Fig. 6. The bottom

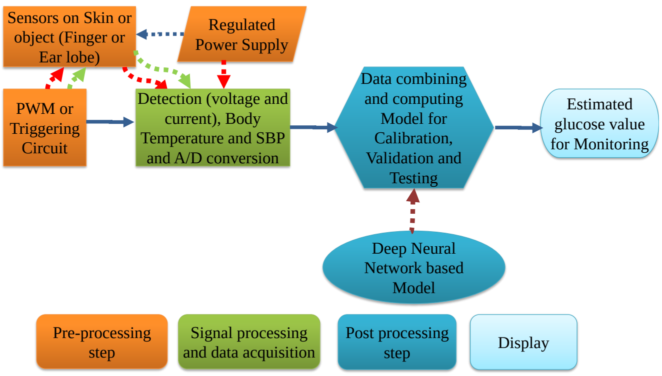


Fig. 6 Processing steps of proposed glucose measurement

flow chart demonstrates the various stages of the upper flow chart. Preprocessing, signal processing & data acquisition and postprocessing steps are explained in the upper flow chart. The processing steps of Fig. 6 represent the processing steps of glucose measurement. But, Fig. 5 represents the overall glucose balance paradigm, where measurement and control both are represented.

5.1 Glucose Prediction model with physiological parameters

DNN-based model is also explored for statistical data analysis, which is generally used to simulate the model. The block diagram of the proposed DNN model is given in Fig. 7. It formulates the complicated relationship between attributes. Here in this proposed model, measured data of five channels are combined through a based model [19]. Biases in neural networks are connected and additional units send data to the correct unit. Biases are inserted to help in bringing the end values. Sometimes, biases can also be connected at the output layer to bring the output values dimension as per the requirement. Here; in the present work, the DNN model has been implemented using MATLAB and bias connection is represented at the output specifically.

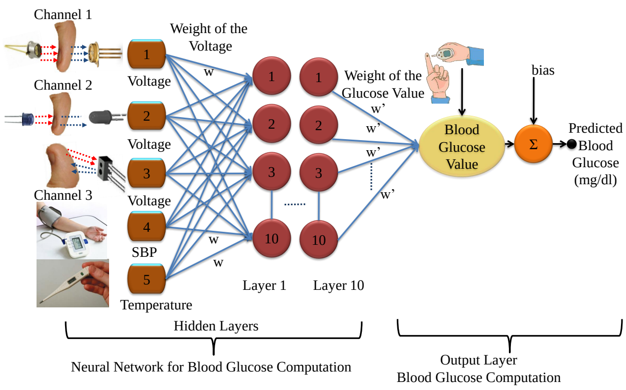


Fig. 7 Block diagram of proposed DNN based model

The explored neural network model combines three inputs from multi-wave NIR spectroscopy and physiological parameters for the precise estimation of blood glucose [27]. The feed-forward back propagation neural network fitting model with sigmoid hidden neurons is used. The total number of nodes in hidden layers is 10. Fig. 8 represents the mechanism of blood glucose prediction using DNN. The complete algorithm is explored for prediction after training the optimized model. The flow chart is shown for measurement purposes. Physiological parameters have been taken to analyze the blood glucose response as these are considered as factors of fluctuations. By involving these parameters, precise glucose measurement is expected in case of other disease problems. All these parameters (body temperature and blood pressure) are taken as decimal values using distinct sensor & device. All inputs are incorporated using the DNN model along with 3-channel voltage values from specific wavelengths. The values have been obtained and brought in a specific range of measurement of glucose values using output bias. The network model is trained with the levenberg-marquardt algorithm [19]. The sample size is 116, from which 34 subjects have been chosen randomly. Randomly selected 34 subjects train DNN model. The model is validated and tested through 10 subjects as per the standard ratio of the model. After applying the proposed DNN-based fitting model, 12.50% mARD, and 12.10% average error are found in predicted blood glucose values. The predicted blood glucose value responses using the based model are represented in Fig. 11. These samples have been taken from people aged 17 to 65. The data has been collected from people in fasting, postprandial and random modes. As per the random data ratio of healthy, hyperglycemia and hypoglycemia patients, 3:2:1 has been analyzed. Apart from 34 training samples, 40 samples were used to validate the device and the remaining 32 samples were taken for testing. 10 specific sample data have been taken randomly to cross-test (random test) the iGLU 4.0.

5.2 Proposed mathematical decision model for glucose balancing paradigm

The ordinary mathematical model provides the decision data to the consultant. The model is constructed with the independent variables such as food intake, insulin data and glucose values. The dependent variables are other parameters which are used to analyze the glucose fluctuations. Eq. 1 [16] represents the glucose level fluctuation as per the time.

$$\frac{dG_{pls}}{dt} = \frac{[G_{gutabs}(t) + NHG(t) - G_{iig}(t) - G_{rnlg}(t)]}{V_{gd}} \quad (1)$$

Here, $G_{gutabs}(t)$ = glucose absorption from the gut, $G_{iig}(t)$ = without insulin glucose, $G_{rnlg}(t)$ = Renal glucose value and V_{gd} = distributed glucose.

The total plasma glucose represents the glucose consumption and insulin concentration [16].

$$G_{iig}(t) = \frac{G_{pls}(c.EI(t) + G_{pls}G_{guii})(k + G_{ref})}{G_{ref}(k + G_{pls})} \quad (2)$$

c= Slope between oral glucose (carbs and food intake) and insulin level, G_{guii} = glucose consumption without insulin effect, G_{ref}= Reference glucose values and $[EI(t)]$= Effective insulin.

The glucose level in the body will be source from food in terms of carbs intake, which is demonstrated below

$$\Delta G_{main} = G_{Emp} - (K_{gabsorb} \times G_{main}) \quad (3)$$

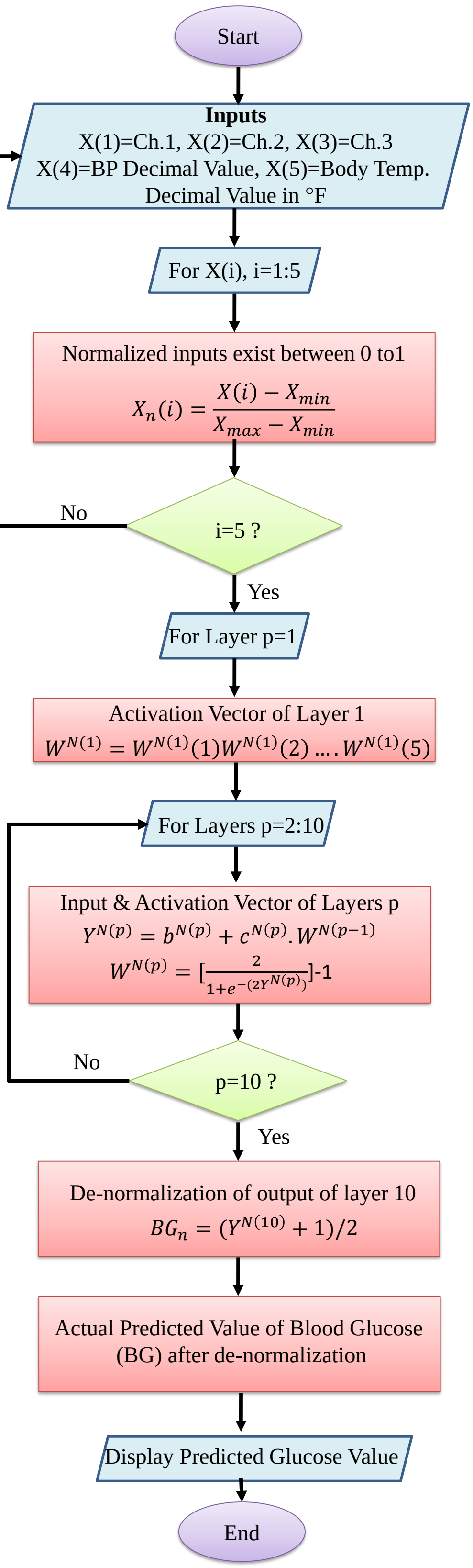


Fig. 8 Flowchart for the prediction of BG with optimized DNN visible mathematical model.

Here, G_{gut}= The body glucose and G_{Emp}= Gastric emptying.
$K_{gabsorb} \times G_{main}$= Glucose consumption for systemic circulation.
The above-represented equations are used to estimate different parameters, which demonstrate the cause of blood glucose fluctuations. These equations analyze the proper cause and help to provide treatment in terms of prescribed diet, medicines and insulin secretion plans so that patients can be better at balancing of glucose levels within a short duration. Using an explored mathematical decision model, glucose-insulin balance could be possible after obtaining multiple parameters. Various steps have been prioritized to represent the glucose balancing paradigm. The presented flow chart explores the various prioritized steps of identifying glucose parameters, insulin level in the body and ratio of food intake and insulin level, which is shown in Fig. 9.

6 Experimental Results

The non-invasive glucose measurement is based on optical detection, where an optimized approach enhances the accuracy level at the desired level. The finger size and different boneless body parts don't affect the blood glucose concentration. To examine this, an experimental analysis is performed, which shows that the SNR ratio is not affected by the change in path length. A person aged 30 has been included for analysis. The blood glucose measurement has been done seven times with time intervals of 2 hours a day. At the same time, the data has been collected from different combinations of fingers and earlobes. During this experimental work, it has been analyzed that different body parts (fingers and other boneless parts) won't affect the accuracy of predicted blood glucose values. The referenced and predicted blood glucose values through different objects are shown in Fig. 10. This is an experimental analysis to validate the glucometer for precise measurement. In the next part of the experimental analysis to validate the proposed glucometer, these 34 samples are randomly taken among 116 male and female samples with their body temperatures and systolic blood pressure values. The graphical representations validate the accuracy of the proposed glucometer with consideration of physiological effects. The predicted and referenced blood glucose values with physiological parameters are shown in Fig. 11.

To quantify the clinical accuracy of estimated blood glucose from the proposed system, it is necessary to compare measured values from the proposed system to the reference values from the conventional blood glucose measurement method. Clarke has elaborated that

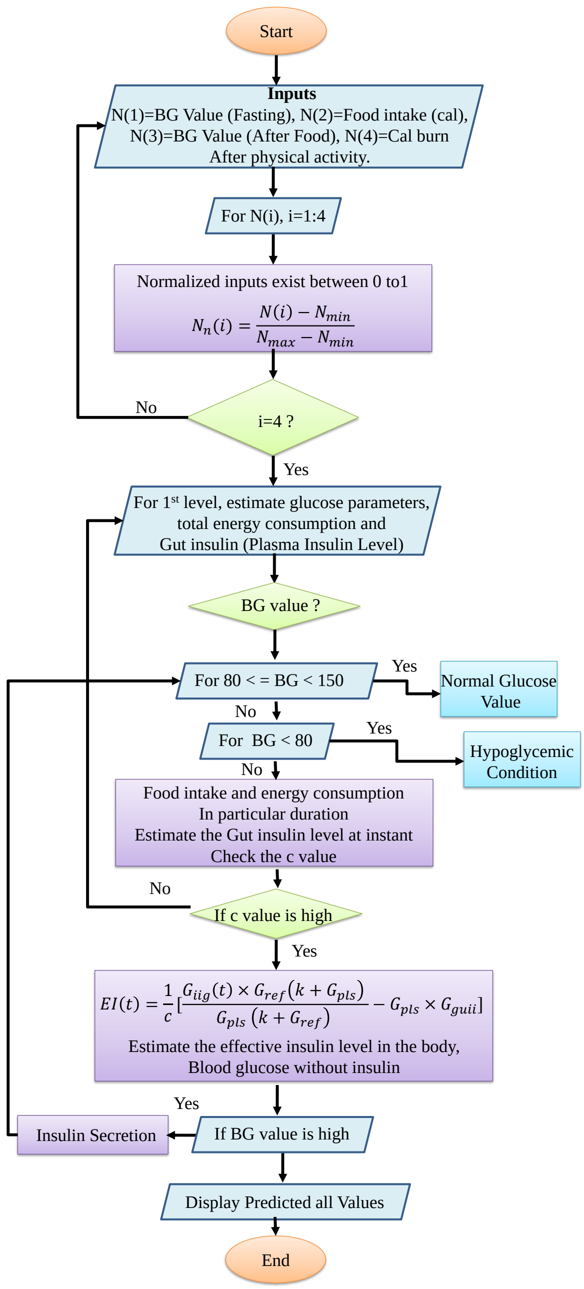


Fig. 9 Flowchart for the mathematical decision model of glucose balancing paradigm.

the values which exist in zones A and B are desirable [28]. During Clarke error grid analysis, it was found that 94.12% predicted values of blood glucose of samples exist in zone A and zone B using the proposed system. The Clarke error grid analysis of predicted blood glucose values is represented in Fig. 12. After analysis of data, it is concluded that the glucose value fluctuates according to these physiological parameters and sometimes, it represents a deviated glucose value from the actual value. The iGLU 4.0 has been enlightened with these param-

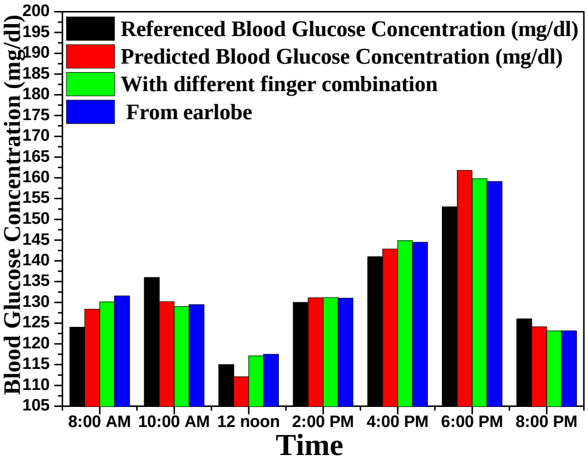
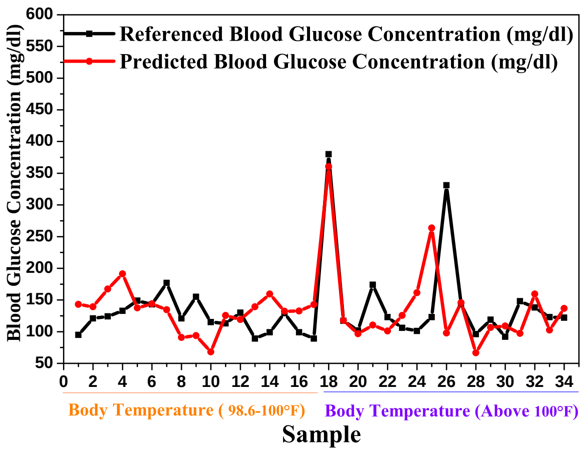
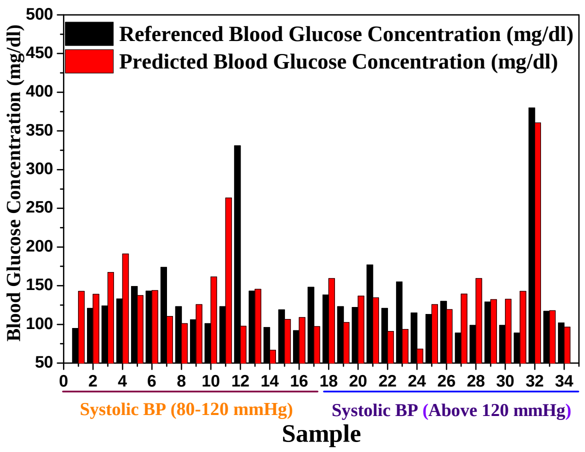


Fig. 10 Predicted and referenced blood glucose concentration values through different objects



(a) with body temperatures



(b) with systolic blood pressures

Fig. 11 Predicted and referenced blood glucose concentration

eters and tried to bring the measurement towards the precision of blood glucose values in the presence of other diseases and problems. The 12.10% error has been analyzed in case of fluctuated body temperature and blood pressure. In future research, the slightly higher error can be overcome by deploying some advanced features in iGLU 4.0.

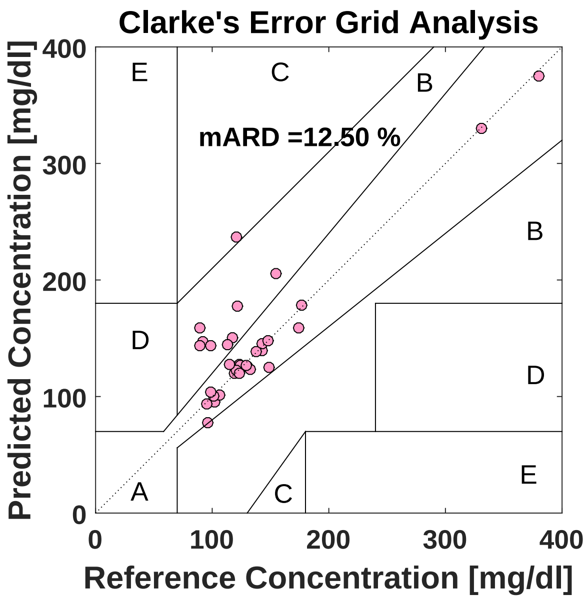
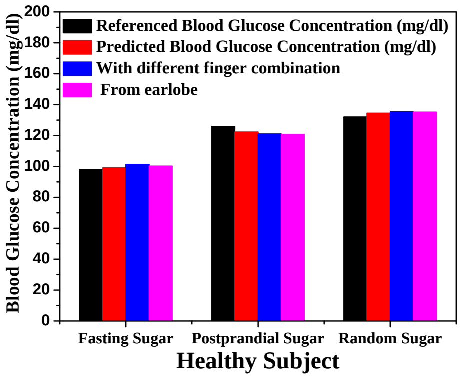
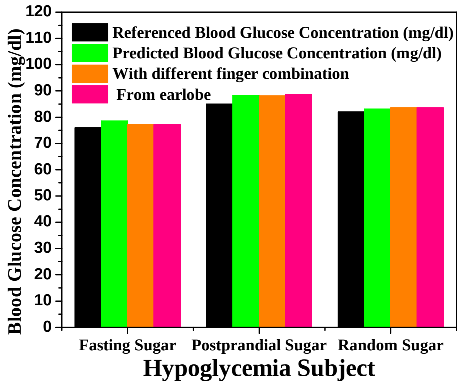


Fig. 12 Predicted and referenced blood glucose concentration using deep neural network based model

Three volunteers were randomly selected to analyze the device stability and results validity, each belonging to the normal, hypoglycemic and hyperglycemic conditions. The precision level of the proposed device is represented in Fig.13. These different types of experimental analysis are required to validate the proposed glucometer for precise measurement with physiological parameters considerations. From a glucose level balancing point of view, experimental analysis is required to validate the proposed paradigm. To perform the experimental analysis, 5 cases are considered from 70 samples (Hyperglycemia). 70 samples are listed for bifurcation of samples who were taking insulin treatment to maintain normal glucose levels. 10 samples are found with insulin-level treatment out of 70 samples. Out of 10 cases, 5 cases have been chosen for keen observation to validate the proposed system. These 5 cases are prescribed with initial scheduled insulin and diet plans as per the expert medical consultant. The carbs intake (food), insulin doses and glucose levels are analyzed for 24 hrs. These values are required to prepare the data by decision model, which would have a model for finding auxiliary parameters. The data is needed to prepare further treatment by medical consultants with less effort, time and stages of treatment. This would be helpful for



(a)



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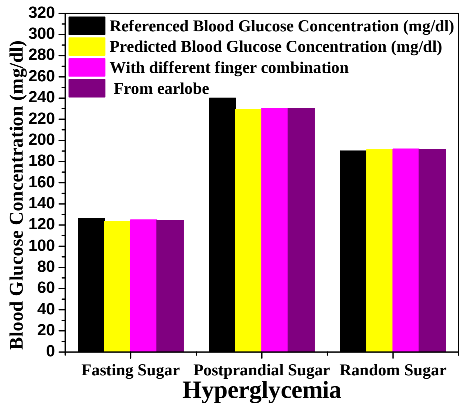

(c)

Fig. 13 Representation of system stability and result validity

the patient to maintain the glucose values at a normal range. 5 cases are represented with different conditions of blood glucose fluctuations and insulin doses at specific times as prescribed. Glucose levels are observed according to the provided different insulin doses and carbs intake. The analysis is represented in Fig 14. The simulated results represented the parameters for further treatment to maintain normal glucose levels. The comparison table represents the proposed work's statistical parameters and technology specifications compared to prior related work. The tabular representation shows the advancement in current work, which is represented in Table 3.

7 Conclusion and Future Direction

The proposed paradigm of glucose balancing consists of precise glucose measurement and estimating physiological parameters. The proposed system provides the feature to generate supporting data, which would be helpful to the expert for the prior level of treatment (prescribed treatment without conventional testing). A multi-wave spectroscopy technique with a unique combination of Physiological parameters based on a non-invasive blood glucose monitoring system is highlighted. The proposed system has the advantage of collecting data without the prior setting of the prototype system for precise detection. The proposed system is a data-demonstrating system to provide better treatment with less effort, time and source usage. Hence, the proposed system will be a comparatively cost-effective solution. The analysis of results has been done in real time. The standard sample collection protocol collects all samples from healthy, hypoglycemic and hyperglycemic patients. The physiological parameters are also considered during sample collection for system validation. It is concluded that the iGLU 4.0 would be capable of measuring precise glucose values after involving physiological parameters. Even though non-uniform combinations of all input parameters would be there. During statistical analysis using proposed computation models, a 0.97 coefficient of determination is calculated using a proposed deep neural network-based model. After analysis, 94% samples have been found in the desired zone. For the advancement of the proposed work, some more physiological parameters must be involved for a precision point of view. Most blood parameters and glucose level values need to be examined for multi-vital monitoring.

In future research, we will design a non-invasive glycated haemoglobin (HbA1c) test system. This blood glucose test indicates your average blood glucose level for the past two to three months. HbA1c test is always considered a preliminary test for type 2 diabetic patients.

8 Conflict of Interest

The authors declare that they have no conflict of interest, and there was no human or animal testing or participation involved in this research. All data were obtained from public domain sources.

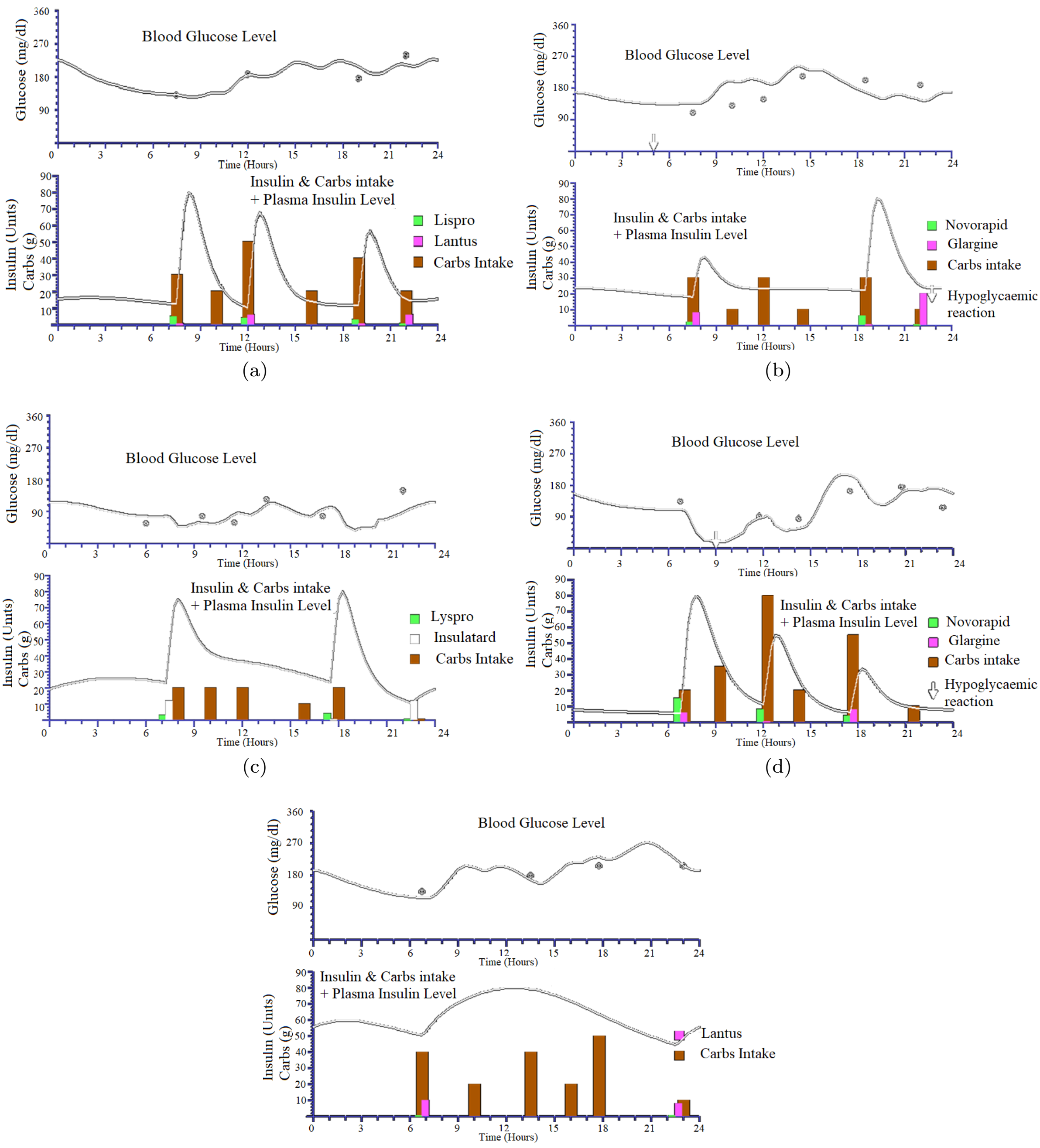

Fig. 14 Analysis of glucose fluctuations with respect to given insulin doses and carbs intake of 5 consecutive cases

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Table 3 Comparison with Non-invasive Works

Works	R^2 value	MARD (%)	Sample /Object	Range (mg/dl)	Application
Singh, et al. [29]	0.8	-	Saliva	90-150	Glucose Prediction
Kirubakaran, et al. [30]	0.91	-	Pancreas	80-250	Glucose Prediction
Joshi, et al. [17]	0.96	12.6	Blood	80-300	BG-Insulin Model
Murad, et al. [23]	-	-	Simulation	-	Glucose Detection
Kirubakaran, et al. [24]	0.91	-	Body	110-400	Glucose Prediction
Mohammadi, et al. [25]	-	-	Body	-	Glucose Detection
Erick, et al. [31]	0.9	-	Capillary Blood	80-330	Glucose Detection
Jain, et al. iGLU [21]	0.95	6.65	Capillary Blood	80-350	Glucose Prediction
Joshi, et al. iGLU 2.0 [22]	0.97	4.86	Serum	80-300	Serum Glucose Prediction
Joshi, et al. iGLU 3.0 [17]	0.90	9.96	Serum	80-250	Glucose Prediction & Security
Proposed Work iGLU 4.0	**0.97**	**12.5**	**Blood+ Body(SBP)+ Temperature**	**80-400**	**Glucose Balancing Paradigm**

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