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An Intelligent Non-Invasive Sweat-Based Glucose Monitoring System for Managing Diabetes Mellitus

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Abstract: In this paper, a non-invasive approach based on Wireless Sensor Networks (WSNs) has been introduced to monitor the glucose level of the patient based on their sweat salt concentration. This developed methodology is painless, economical, and simple for effective management of Diabetics. The responses are examined to monitor the increased sweat salt concentration that causes high glucose levels. Low amounts of glucose are the result of low salt content in perspiration. By using an interpolation equation, it is possible to correlate the salt content of sweat with its related voltage and glucose level. The proposed system is designed and simulated using the proteus software and the hardware implementation is carried out for continuous monitoring of glucose level which involves the collection of anonymous data of 8 different patients belonging to different age groups. For the qualitative analysis, the response from the hardware is verified against the clinical results through Parkes Error Grid Analysis tool.

Keywords: *Continuous Glucose Monitoring System,Non-Invasive method, Blood Glucose, Diabetes, Wireless Sensor Network (WSN).*

1. Introduction

Evolution of Glucose monitoring started off in the year 1960, were the first generation glucose sensors were introduced made of enzyme based electrodes. After the discovery of insulin, insulin pumps were used to deliver the insulin. First test strip named Dextrostix made from glucose oxidase was developed in the year 1965. Around 1970 glucose meters were developed that constitutes the second generation of glucose monitoring system. Third and fourth generation paved way for the development of enzyme free, fiber optic, wearable, mass sensitive device with implantable amperometric biosensors. With the advent of nanomaterial biosensor, commercial sensors were introduced in the fifth generation which is capable of real time tracking, continuous and painless monitoring, generating trends and patterns of glucose levels.

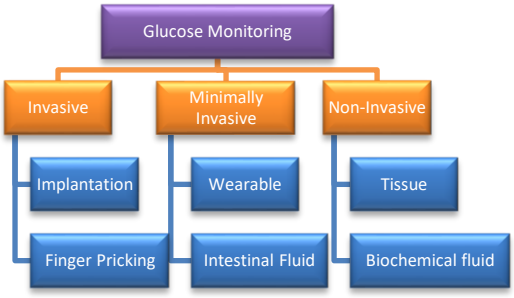

Fig 1. Types of Glucose Monitoring techniques

Three types of glucose monitoring techniques [27] is depicted in Fig 1 such as,

- Invasive method,
- Non-Invasive method and
- Minimally Invasive method

Invasive method is more painful than the other two methods which involve full implantation or finger pricking process. Fingertip pricking causes discomfort in patients and has the potential to infect the skin. In some circumstances, monitoring the glucose level may be challenging, particularly if the patient is a kid, an elderly person, or one with numerous other health problems. Minimally Invasive method is based on wearables and intestinal fluids. Non-Invasive method includes measure of glucose level either based on the tissue (skin, oral mucosa, tongue) or from the fluids (sweat, tears, saliva, urine). With sweat-based glucose monitoring, people can monitor their glucose levels without the need for a finger prick, which can improve their quality of life and overall diabetes management.

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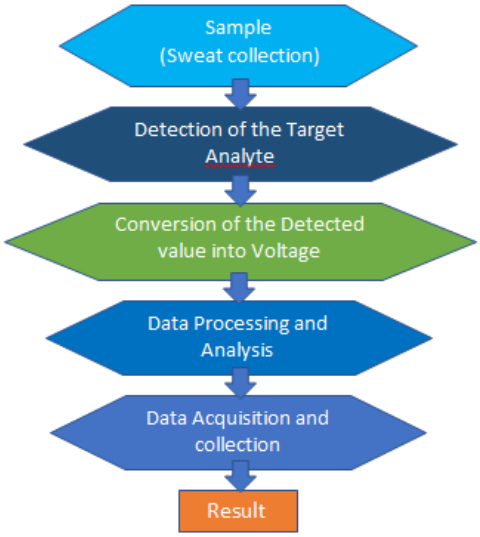


Fig 2. Workflow of Biosensor

Several biochemical markers such as tear, saliva, skin intestinal fluid, sweat and urine are used as analyte in analyzing the glucose concentration. The glucose monitoring devices developed based on these biochemical fluids are represented in Table 1 with their sensitivity and correlation measures. Tear provides less accuracy rate because of the impurities and the difficulty in isolating the glucose from the bio fluids. Saliva is largely affected by the last meal consumed by the patient that could provide inaccurate readings. Skin Intestinal Fluid (ISF) is the extracellular fluid that covers the tissues and requires injection of a small needle to measure the glucose level [16] and urine is not used because of its less accessible nature.

Table 1. Glucose Monitoring Systems based on sweat, ISF, Tears and Saliva

ANALYTE	MERITS	DEMERITS	CORRELATION	SENSITIVITY	ARTICLE
Sweat	Non-invasive Many sample sites Less intuitive	Hysteretic	0.99	23.72 µA mM^{-1}	QingfengZhai [17]
ISF	Non-invasive	Hysteretic Sensitive on skin	>0.9	130.4 µA mM^{-1} 158.0 µA mM^{-1}	Yihao Chen [18]
Tears	Non-invasive	Hysteretic Precision issue	0.94	0.421 µA mM^{-1}	DeonirAgustini [19]
Saliva	Non-invasive	Hysteretic Less correlated Less sensitive	0.99	26.6 µA mM^{-1}	Wenjun Zhang [20]

Irrespective of the analyte being used for the detection of the glucose concentration, the working principle behind the biosensors remains the same. The working principle behind the biosensor as shown in Fig 2, is initiated with the sample collection that can be any biochemical fluids. The collected samples act as an analyte which are recognized in the second layer. Transducer layer includes various transducer such as electrochemical, mechanical, and electrical which converts the detector response into measurable response and finally the results are produces [15]. These sensors are high beneficial to the diabetic

patients in leveraging their lifestyle while managing their glucose level.

2. Comparative study of existing system

Diabetes is a chronic endocrine disease that occurs due to an imbalance in glucose levels and an altering carbohydrate metabolism. It is a leading cause of morbidity, resulting in a reduced quality of life even in developed societies, primarily affected by a sedentary lifestyle and often leading to mortality. Keeping track of blood glucose levels noninvasively has been made possible due to diverse breakthroughs in wearable sensor technology coupled with holistic digital healthcare. Efficient glucose management has been revolutionized by the development of continuous glucose monitoring sensors and wearable, non/minimally invasive devices that measure glucose concentration by exploiting different physical principles, e.g., glucose oxidase, fluorescence, or skin dielectric properties, and provide real-time measurements every 1–5 min [1].

A highly novel and completely non-invasive sweat sensor platform technology that can measure and report glucose concentrations from passively expressed human eccrine sweat using electrochemical impedance spectroscopy and affinity capture probe functionalized sensor surfaces was proposed by DevangsinghSankhala. The sensor samples 1–5 μL of sweat from the wearer every 11 1–5 min and reports sweat glucose from a machine learning algorithm that samples the analytical reference values from the electrochemical sweat sensor [2]. As sweat sensors have garnered much interest in recent years, Elena V. Karpova et al attempts to summarize recent developments in noninvasive continuous glucose monitoring using sweat sensors based on different approaches with an emphasis on the devices that can potentially be integrated into a wearable platform [3]. James Moyer et al came up with a technique that monitors diabetes through continuous analysis of undiluted sweat immediately after its excretion using a flow-through glucose biosensor. The dynamics of sweat glucose concentration, recorded by means of the proposed biosensor, is in good accordance with the dynamics of blood glucose content without any time delay, thus offering a prospect for noninvasive monitoring of diabetes [4].

A perfusion method was used to rapidly harvest sweat from forearm sites on human subjects. The sweat samples were analyzed for glucose by high-performance liquid chromatography methods and compared with the results obtained with a blood glucose meter. The results of 23 different studies of seven individual subjects with diabetes show a strong correlation 13 between sweat glucose and blood glucose [5]. Pei-Henglin presented awearable/disposable sweat-based glucose monitoring device integrated with a feedback transdermal drug delivery module. Careful multilayer patch design and miniaturization of sensors increase the efficiency of the sweat collection and sensing process [6]. Although most sweat glucose sensors have targeted applications during exercise and other active stimulation induced-sweat, natural sweating offers an attractive alternative with minimal effect on users that can be accessed during routine and sedentary activities without impeding personal lifestyle and preserves the correlation between blood and sweat glucose. Here, we present a noninvasive sweat glucose sensor with convenient hydrogel patches for rapid sampling of natural perspiration without external activities that stimulate sweating. The wearable hydrogel patch rapidly takes up natural sweat from the hand and serves as a medium for electrochemical sensing [7]. Mobile colorimetric wearable biosensors that measure glucose levels in sweat are ideal for self-monitoring as they can utilize the camera in smartphones for signal reading. However, colorimetric biosensors proposed thus far have higher limit of detection (LOD) than electrochemical devices, which makes them unsuitable for detecting hypoglycemia [8].

3. Non-Invasive Glucose Monitoring System

An intelligence sweat-based glucose monitoring system is an innovative technology that has the potential to improve the lives of people with diabetes by providing a non-invasive and convenient way to monitor their glucose levels. There are several techniques to measure the glucose level from the sweat samples that includes enzymatic reactions, optic methods, and electrochemical methods. This work focuses on electrochemical method of measuring the glucose level in a person's sweat through Wireless Sensor Network. The system would use Parkes Error Grid tool to analyze the data from the sensors and provide real-time feedback and recommendations to the user. The functionality of the entire work is shown in the Fig 3. The Node MCU unit is the system's primary controller, or microcontroller. The user sets commands for the operation of the appliances using the mobile application. In speech or switch mode, the mobile application interprets the user's command and transmits a signal to the Node MCU unit via a wireless network set up byWi-Fi communication. The Wi-Fi module, which is embedded inside Node MCU, aids the microcontroller in connecting to a device through Wi-Fi and accept orders from an application across the wireless network.

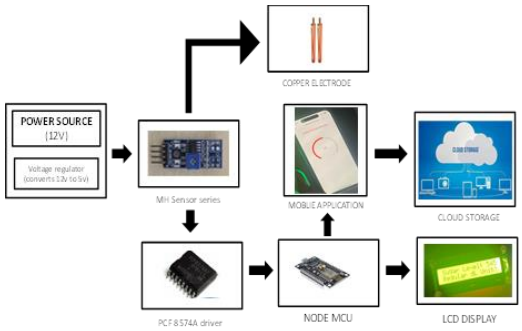


Fig 3. Block diagram of the proposed system

A) COMPONENTS OF CGM SYSTEM

The components of the CGM System are detailed as follows,

1. ***MH Sensor Series*** – This sensor is intended to detect the placement of the finger through the intensity of the infrared light reflected from the skin surface. This sensor works in both digital mode and analog mode and the output of the analog mode provides the intensity of the glucose level in sweat.
2. ***PCF 8574A Driver*** **–** This driver is used to interface the external devices by extending the input/output ports of the microcontroller using GPIO (General Purpose Input/Output) pins of the host controller.
3. ***Copper Electrode*** **–** Copper electrodes are used as cathodes for the electrochemical process in potentiometric measurements. Affordability, corrosion resistance, stable connection, and high conductive nature makes copper electrodes more suitable for the proposed methodology.
4. ***Cloud Storage*** **–** The data gathered from the CGM system using the Wireless Sensor Network (WSN) is sent to the cloud for storage, easy access and retrieval. The gathered data is first processed and formatted before sending it to cloud for analysis. A communication protocol is established to connect and transfer the data from the sensor to the cloud after which the data is subjected to analysis and predictions.
5. ***LCD Display*** **-** LCD display is used in many modern devices to display the visuals in vibrant form. This device provides high quality output with less power consumption. The output of the CGM system measuring the glucose level of the patient in mg/Dl is displayed onto the LCD display.
6. ***Node MCU*** **-** Node MCU is an open-source platform based on ESP8266 Wi-Fi that provides easy connectivity of components such as voltage regulators, USB-to-serial convertor, and other devices in a versatile manner. It provides seamless connection over the internet by establishing a convenient solution for Wi-Fi connectivity.
7. ***Mobile Application*** **–** Blynk Application is used to display and visualize the data remotely. Drivers are installed for interfacing the hardware. Blynk servers are responsible in establishing the communication between the mobile phones and the hardware.

B). FRAMEWORK OF CGM SYSTEM

The schematic flow of the proposed CGM system is illustrated in Fig 4. The proposed framework consists of sweat detection system that collects the sweat sample and detects the glucose level using the electrochemical process. Further the data is analyzed using Parkes error grid tool for proving the accuracy rate.

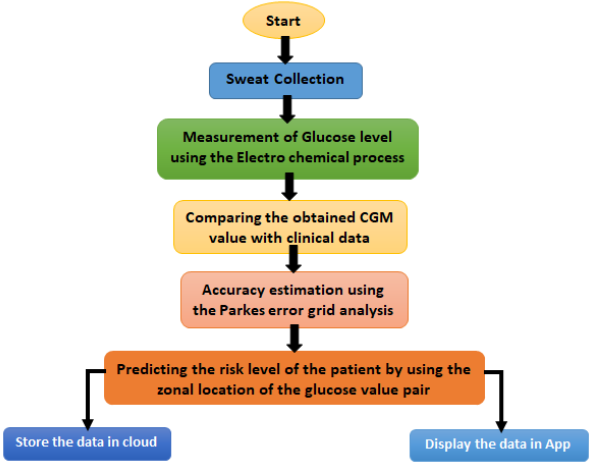


Fig 4. Flowchart of the proposed methodology

(i). Sweat collection: Among all the biochemical markers, sweat is the top contender, because sweat glands are present all over the body and are more in prominence at the forehead, armpit, palms, and soles of the feet [11,12] as depicted in Table 2. Sweat is composed of water, electrolytes and various other metabolites like glucose. Sweat is considered as an alternate analyte for glucose monitoring though the correlation between the glucose level in the sweat and that of blood is not direct. Glucose present in the blood travels through the blood vessels into the underlying skin tissues to the sweat glands. The glucose concentration is influenced by glucose level, sweat gland activity, and sweat rate.The concentration of glucose present in the blood is comparatively higher than that of sweat. Still sweat has a greater potential in providing insights about the glucose trends and changes because it is,

- Easily collectable
- Least intuitive solution
- More sampling sites
- Consistent access
- Sweat glands are highly vascularized
- Freely available
- Non invasive

Besides these advantages there are few challenges in using sweat as the biomarkers of glucose that includes low production rate, contaminations from the skin due to dead cells and sebum, temperature, sweat gland periodic activation and sampling variability between and within the samples due to adaption to new environment [21,22], physical development [23,24] hydration [25] and diet [26]. The amount of glucose present in the sweat differs from 0.06 to 0.2 mM [9,10].

Table 2. Sweat intensity of the body parts

BODY PARTS	SWEAT INTENSITY
Palm	310
Sole of the foot	300
Abdomen	225
Chest	225
Backside of the hand	170

(ii). Glucose Measurement: Copper-clad sheets would be applied to the skin that would draw salt from perspiration using a technique known as reverse iontophoresis. With the aid of an external power source, current will flow between the copper electrodes and sodium ions present in the salt. The quantity of sodium ions in the sweat fluctuates according to blood glucose levels, and the conduction varies according to the sodium ions present in the sweat. Therefore, based on the conduct of respective register, value is activated, and the corresponding glucose level is obtained. Changes in the analyte concentration is demonstrated by the changes in the electrochemical potential measured by the biosensor. The relationship between the concentration of the analyte (C) and the electrochemical potential (E) is measured using the Nernst equation as,

$$E = E_O - \left(\frac{RT}{nF}\right) * In(C) \qquad (1)$$

where E is the measured voltage of the electrode, E_O measures the potential of the analyte at its reference value, R represents constant, T denotes temperature in kelvin, n indicates the number of electrons transferred as a result of the reaction, F is the Faraday constant denoting the charge per mole of the electrons.

The enzymatic reaction that takes place during the glucose sensing process is represented as,

$$Glucose + 02 \rightarrow Gluconic\ Acid + H_2O_2 (2)$$

where the glucose in the presence of glucose oxidase is oxidized to produce gluconic acid and hydrogen peroxide. The produced hydrogen peroxide is then used to measure the concentration of the glucose through the oxidation process,

$$H_2O_2 \rightarrow 2H + O_2 + 2e^- (3)$$

The current generated during the process of oxidation is directly proportional to the concentration of the hydrogen peroxide from which the glucose concentration is relatively identified. The relationship between the current and the concentration of the glucose is graphically illustrated in Fig 5.

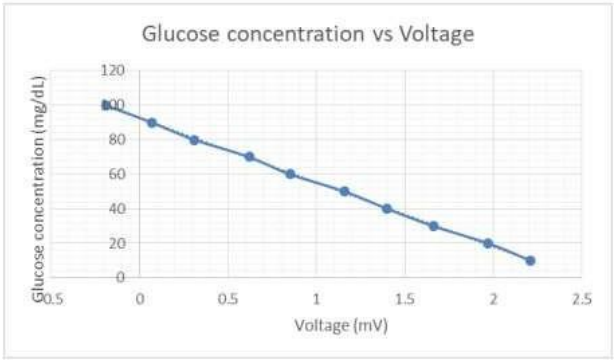


Fig 5. Correlation of Voltage and Glucose concentration

Fig 6 highlights the cross sectional view of the non-invasive glucose monitoring system along with their sensing layers. The sensing component of the CGM system is being placed directly on the skin and the subsequent enzymatic reactions takes place withIN the system and finally the results of the glucose readings are displayed on to the users UI.

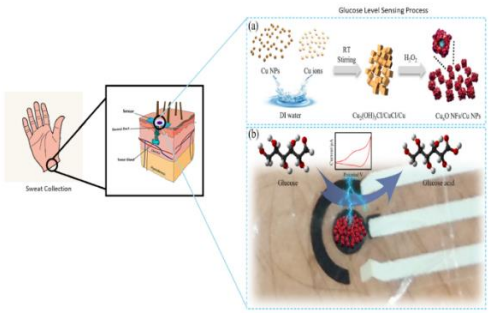


Fig 6. Process of glucose detection from sweat

(iii). Data Analysis: Blood sugar levels can change based on several variables, including age, the time of day, physical activity, and food intake. However, the various blood glucose ranges is represented in Table 3 and discussed as follows,

(a). Normal fasting blood sugar: 70 to 100 mg/dL (3.9 to 5.5 mmol/L).

(b). Impaired fasting glucose (IFG): 5.6 to 6.9 mmol/L or between 100 and 125 mg/dL. This denotes a blood glucose level that is higher than usual but not high enough to be classified as diabetes.

(c). Diabetes: is characterized by fasting blood glucose levels of 126 mg/dL (7.0 mmol/L) or greater on two different tests.

(d). Postprandial glucose levels: Following a meal, blood sugar levels may momentarily rise. Two hours after a meal, postprandial blood glucose levels should be less than 180 mg/dL(10 mmol/L).

(e). Hypoglycemia: or low blood glucose, is indicated by blood glucose levels under 70 mg/dL(3.9 mmol/L). Hypoglycemia can cause perspiration, disorientation, and dizziness.

It is vital to remember that target blood glucose levels can change based on a person's unique situation and health. A healthcare professional should always be consulted for specific advice on controlling blood glucose levels.

Table 3. Ranges of the blood glucose level

Salt Level	Register Value	Voltage	Sugar Level	Type
17	<200	0.65	<53	High Hypoglycemia
35	201-400	0.65-1.28	54-70	Hypoglycemia
51	401-600	1.28-1.9	71-125	Normal

72	601-800	1.9-2.37	125-200	Hyperglycemia
91	801-1023	2.37-3.3	201-500	Metabolic Crash

(iv). Output and Display: The proposed system would offer several benefits to people with diabetes, including real-time feedback on glucose levels, personalized recommendations for controlling glucose levels, and the ability to track glucose levels over time. The system could also be used to provide medical practitioners with more detailed information on their patient's glucose levels, allowing for more effective treatment plans. The open-source functionality is flexible and available with the Android OS. It is simple to access the built-in sensors. The following features are present in the system control application. The Android phone serves as a client and sends data via socket programming.

(a). User interface: The user interface would provide the user with real-time feedback on their glucose levels, as well as recommendations on diet and exercise to help control their glucose levels. The interface could be in the form of a mobile app (BLYNK Application) or a display on the data analysis device. The BLYNK Application's working operation is represented in Fig 7.

(b). Cloud storage: The system includes cloud storage for storing the user's glucose data over time. This data could be used to track the user's glucose levels over time and provide personalized recommendations based on their history.

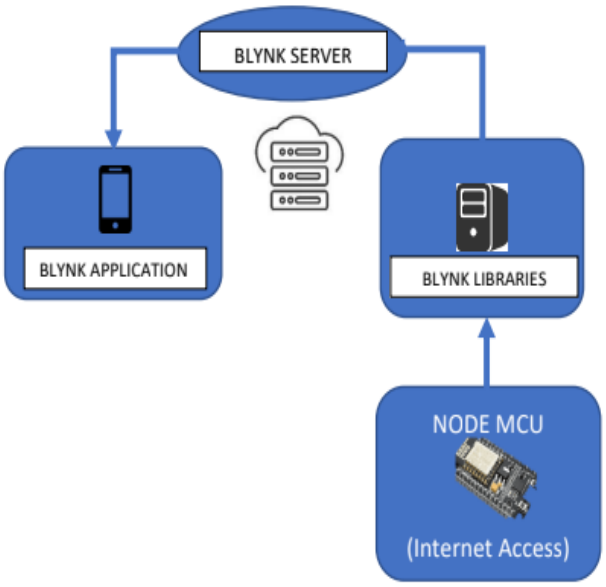


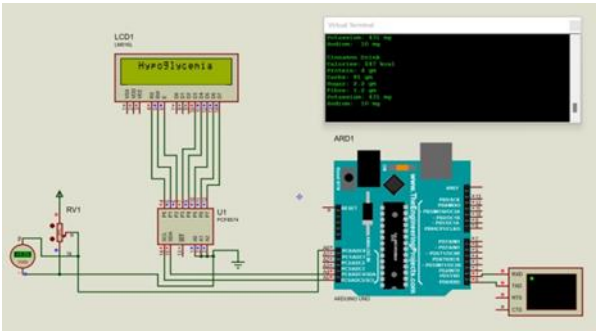
Fig 7. Working principle of the Blynk Application

4. Result and Discussion

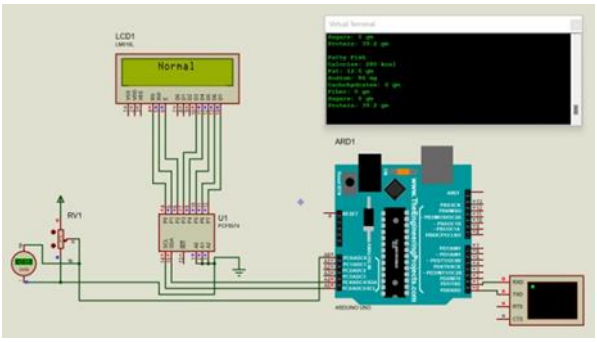
The performance of the proposed CGM system is studied using the simulation and based on the simulated test system the hardware is developed. The sample data is collected from 8 different patients and the simulation study is investigated using the Proteus Design Suit V8.12.

A) SIMULATION STUDY

The simulation is carried out using the sample data of 8 different patients. The simulation setup is developed using the Arduino board, PFC8574 general-purpose remote I/O and to display the output values the LCD Display is added. The screenshot of the simulation results obtained from the Proteus software is shown in Fig 8 (a). (b), (c), (d) indicating the 4 different condition of the glucose level such as Hypoglycemia, Normal, Diabetic and Severe Hypoglycemia respectively.



(a)



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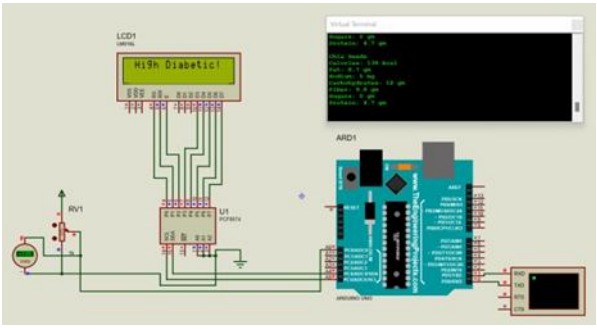

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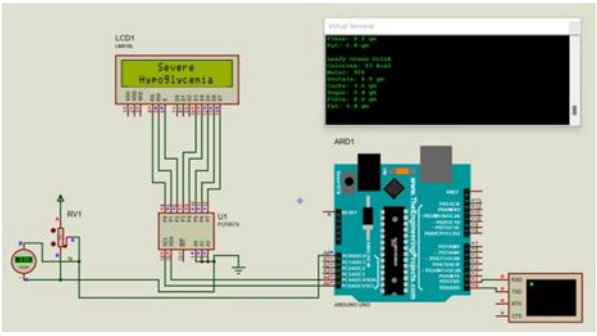


(d)

Fig 8 (a), (b), (c), (d). Simulation results of the proposed CGM system from Proteus software

(i). Case 1- Hypoglycemia: Under this case the blood glucose level is under 70 mg/dL(3.9 mmol/L). The simulation data shows the status as Hypoglycemia which represents that the patient is having low glucose level suggesting them to eat or drink 15 to 20 grams of fast-acting carbohydrates (cinnamon drink) to stabilize their glucose level.

(ii). Case 2-Normal blood sugar: In this scenario the blood glucose level lies between 70 to 100 mg/dL(3.9 to 5.5 mmol/L). The simulated data represent the condition as Normal, which means the glucose level in the body is balanced.

(iii). Case 3-High Diabetic: In this case, the glucose level ranges from 5.6 to 6.9 mmol/L or between 180 and 200

mg/dL. This denotes a blood glucose level that is higher than usual, consuming of high fiber (Chia seeds) in regular diet and keeping the body hydrated / (Visiting a doctor) is notified in the display.

(iv). Case 4-Severe Hypoglycemia: In this condition, the hypoglycemia becomes severe, patient is not recommended to undergo regular eating habits. At this point, your blood glucose level is less than 54 mg/dL—often below 40 mg/dL. Immediate consumption of green tea and hospital visit is suggested by the simulation.

Based on the simulation study the hardware is designed and developed, the upcoming section describes the proposed control strategy which is validated with the hardware setup and the results are compared with real time clinical laboratory data.

B). HARDWARE SETUP

The system is designed, tested, and simulated based on real time data obtained from the patients which are then deployed in the hardware system for validation. Errors are debugged at the simulation stage to improve the reliability and accuracy of the experimental setup.

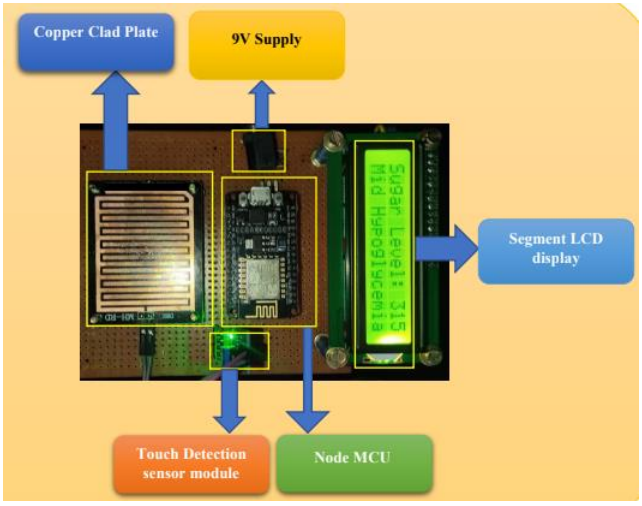


Fig 9. Hardware setup of the CGM system

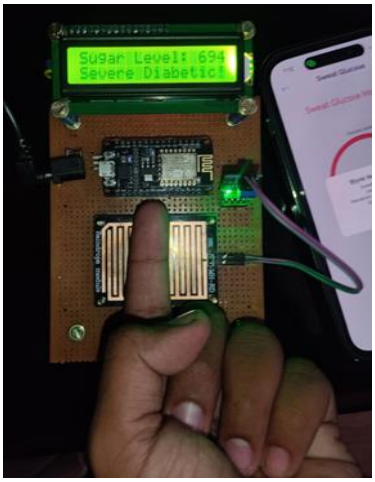
The Fig 9 shows the Hardware setup of the proposed CGM system, the technical specifications of the hardware setup is shown in Table 4. Copper clad plate are used as cathodes for the electrochemical process in potentiometric measurements. The copper plate acts as a variable resistor and its resistance varies with respect to the sweat salt level. The proposed method uses copper electrodes which are more suitable for sweat detection and maintains better accuracy in prediction. The copper electrode is incorporating with touch detection sensor module, The sensor module consists of a potentiometer, LN393 comparator for sensing the human touch and sends the signal to Node MCU. Node MCU acts as a microcontroller for processing and the processed output of the CGM system measuring the glucose level of the patient in mg/Dl and is displayed onto the LCD display. The gathered data is sent to the cloud for storage, easy access, and retrieval. By using the BLYNK application the stored cloud data can be view and notified to patients.

Table 4. Hardware Specifications

S.No	COMPONENTS
1	ESP32 Master
2	LM324 OP AMP
3	9V Supply
4	PCF 8574 I2C LCD
5	Voltage Regulator
6	Copper Clad Sheet for Glucose Level Test
7	Node MCU

C). EXPERIMENTAL RESULTS

In this section the proposed controller is validated with the experimental setup and the results are achieved from the experimental setup. The hardware output shows the status of the patient such as Severe Diabetics (Condition 1), Mid Hypoglycemia (Condition 2) and Normal (Condition 3) as shown in Fig 10.



(a)

(b)

(c)

Fig 10. Output of sweat-based glucose monitoring system

The data gathered is not only displayed and stored in the cloud platform, but also notified in the smart phone connected with the controller through the Wi-Fi module for easy and seamless monitoring. The BLYNK application is connected to the cloud platform and notification of the glucose level is displayed in the app as shown in Fig 11.

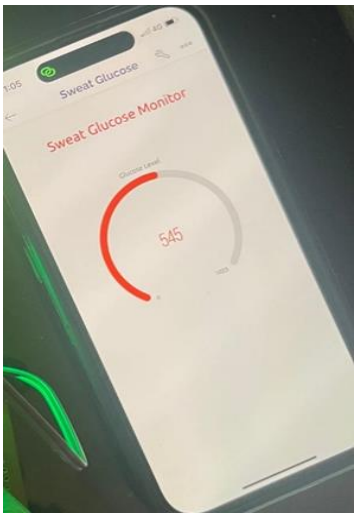


Fig 11. Screenshot of the Blynk Application

5. Conclusion

In this paper, the proposed non-invasive continuous glucose monitoring system monitors the human sweat glucose concentration and reduces the pain of daily needles and blood collection for blood glucose testing. At the same time, the glucose readings are stored in the database of the cloud platform, and remote medical treatment can be realized through the web and API, which can provide valuable data for big healthcare. The accuracy of the proposed non-invasive continuous glucose monitoring system is visually represented using Parked Grid Analysis from which the relationship between the measured glucose level and the clinical outcomes are identified [13,14]. The error rate between the predicted value (Ei) fetched from the proposed methodology and the observed value (Oi) fetched through the clinical tests are estimated. This technique is mainly used to discover the accuracy rate of the CGM system against their clinical tests in a graphical form. The entire grid is segmented into five different zones A, B, C, D, E and each zone corresponds to different level of clinical risks as show in Table 5. Each pair of value is plotted against the grid and the corresponding zone is located. From the zonal location, we calculate the qualitative accuracy which aids in decision making and clinical impact of measurement errors. Through this technique the health care professionals can easily identify the areas of inaccuracies and improve the glycemic control of the patients in managing the diabetics. Fig 12,13 and 14 it is evident that all the values fall under Zone A indicating that the predicted values from the proposed methodology does not deviate much from the observed values and are accurate enough with minimal errors thus proving the proposed methodology to be fit for glucose level monitoring.

Table 5. Zone and its corresponding risk levels

ZONE	RISK LEVEL
A	Accurate measurements
B	Acceptable and safe
C	Requires overcorrection/undercorrection
D	Dangerous
E	Implausible

Table 6. Observed and predicted value of Glucose levels with their zonal location

Patient	TRIAL - I			TRIAL - II			TRIAL - III		
ID	**E1**	**O1**	**Z1**	**E2**	**O2**	**Z2**	**E3**	**O3**	**Z3**
P001	63	68	A	74	70	A	78	76	A
P002	70	65	A	65	65	A	54	50	A
P003	80	85	A	92	90	A	111	110	A
P004	128	125	A	132	130	A	125	127	A
P005	52	50	A	56	52	A	58	53	A
P006	142	138	A	92	89	A	70	73	A
P007	54	54	A	53	55	A	62	60	A
P008	135	130	A	142	139	A	144	139	A

T – Trial, E – Predicted value, O – Observed value, Z – Zone

In table 6, E1, E2 and E3 represents the predicted value of the patients in three different trials T1, T2 and T3. Similarly, O1, O2 and O3 denoted the observed value of the glucose obtained from the clinical test in three different trials. For instance in the first trail T1 for the first patient with PID P001, EI = 63 is the predicted glucose level and O1 = 68 is the observed value from the clinical test.

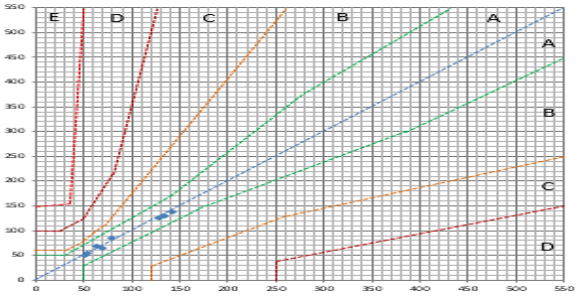


Fig 12. Parkes Error Grid for Trial I

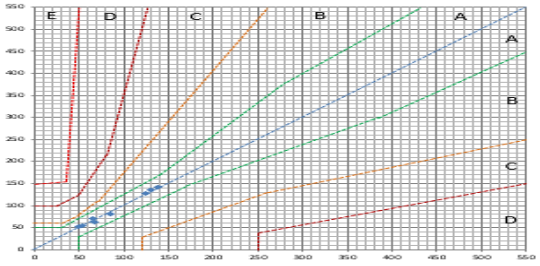


Fig 13. Parkes Error Grid for Trial II

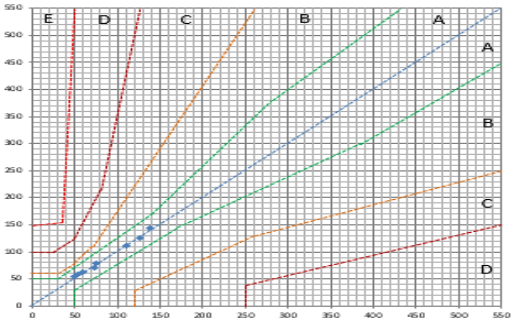


Fig 14. Parkes Error Grid for Trial III

For managing diabetes, an intelligent sweat-based glucose monitoring device has produced encouraging results. The technology offers a non-invasive method of measuring blood glucose levels, which may increase adherence to testing and diabetes management. The following are a few advantages of this system,

(i). Improved accuracy: Sweat-based glucose monitoring system proves to be as accurate as traditional blood glucose monitoring methods. This means that people with diabetes can rely on the system to provide accurate data about their glucose levels.

(ii). Convenience: The system is non-invasive, meaning that people with diabetes can monitor their glucose levels without the need for a finger prick. This can improve compliance with monitoring and overall diabetes management.

(iii). Real-time monitoring: The data collected by the monitoring system is sent wirelessly to a mobile device or computer, allowing people with diabetes to monitor their glucose levels in real-time. This can help them to adjust their diet, exercise, or medication to keep their glucose levels in a healthy range.

(iv). Personalized care: The data collected by the monitoring system can be used to provide personalized care for people with diabetes. Healthcare providers can use the data to track changes in glucose levels over time and adjust treatment plans accordingly.

Overall, intelligence sweat-based glucose monitoring system has the potential to improve diabetes management by providing a convenient and accurate way to monitor the glucose levels. The evaluation of the proposed work with different patient's data is carried out under the simulation study and real time hardware setup. After the implementation of this intelligent system, promising and effective results are achieved and also the gathered data is evaluated with the real time clinical results to prove its accuracy and reliability.

Author contributions

Harshini Manoharan: Conceptualization, Methodology, Software, Field study **Dhilipan J:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Saravanan A:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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