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INVITED PAPER

Internet of Things Based on Electronic and Mobile Health Systems for Blood Glucose Continuous Monitoring and Management

JOSÉ JORGE RODRIGUES BARATA¹, ROBERTO MUNOZ², (Member, IEEE),
RAFAEL D. DE CARVALHO SILVA¹, JOEL J. P. C. RODRIGUES^{3,4}, (Senior Member, IEEE),
AND VICTOR HUGO C. DE ALBUQUERQUE¹, (Senior Member, IEEE)

¹Graduate Program in Applied Informatics, University of Fortaleza, Fortaleza 60811-905, Brazil

²Escuela de Ingeniería Civil Informática, Universidad de Valparaíso, Valparaíso 2362735, Chile

³Department of Electrical Engineering, Federal University of Piauí, Teresina 64049-550, Brazil

⁴Instituto de Telecomunicações, 3810-193 Aveiro, Portugal

Corresponding author: Joel J. P. C. Rodrigues (joeljr@ieee.org)

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ABSTRACT Over 425 million people suffer from diabetes worldwide and this number is expected to increase over the years. Rigorous and extensive research has led to the development of increasingly advanced technologies, such as continuous glucose monitoring and glucose flash monitoring. These new technologies are more promising and efficient with respect to calculating the glycemic index and are more easier to use than the glucometer technology already established in the market. However, market solutions are often highly restrictive due to their costs. In an effort to address this challenge, this article describes the Freestyle Free sensor and the associated advantages of an integrated and low-cost environment that it offers patients. The proposed environment allows continuously monitoring the blood glucose rate and provides doctors and caregivers information remotely. Additionally, the data generated will allow the application of data mining techniques in efforts aimed at understanding the disease better. The integration between the patient and the integrated environment occurs through the near-field communication sensor over an Internet of Things card, which sends the data collected for the LibreMonitor mobile application. To evaluate the integrated environment, we compared the glucose rates measured with an official Freestyle Libre software during the same period. Based on the positive results, we propose that the integrated environment is a low-cost alternative for continuous glucose monitoring of patients with diabetes.

INDEX TERMS Diabetes mellitus, data mining, Internet of Things, Internet of Health Things.

I. INTRODUCTION

According to the International Diabetes Federation, over 425 million people were diagnosed with diabetes in 2017. By 2045, this number will increase to 629 million, with a projected rise of 130,000 cases each year; over one million of these cases are expected to be children and adolescents [1].

Genetic factors and lack of control over glucose are the primary causes of diabetes since these are responsible for micro and macrovascular complications, thereby resulting

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in an increase in morbidity and mortality and causing over 4 million deaths in 2017 and 612 billion dollars in health care expenses [2], [3].

Diabetes is life threatening or can incapacitate a person, imposing an enormous economic expense on governments and exceeding the resources invested in the health systems. The health sector is interested in meeting important goals for diabetic patients such as the improvement of clinical outcomes and patient care in order to upgrade clinical outcomes; real-time measurement and disease management are considered integral factors in the improvement of patients' life quality [4].

Although a cure is not available yet, diabetes can be effectively managed through the regular evaluation of blood glucose levels and through the continuous monitoring of daily shots. Glucose self-monitoring is considered an effective tool for this purpose, especially for patients with type 1 diabetes (T1D). Unlike other diabetes patients (for example, gestational and T2D), T1D patients are insulin dependent and will depend on glucose control and application of insulin for life; hence, the disease currently has no cure. Children and adolescents with T1D depend exclusively on self-testing to manage and maintain control over the disease. However, unlike children with other chronic diseases, children with diabetes T1D must accept needles as a part of their daily lives. Needles, the fear of pain and blood, and the injuries caused tend to make self-testing less frequent and, consequently, glycemic control is affected. Self-testing and daily maintenance of blood glucose is highly important for resolving the risk of hyper- and hypoglycemia, which can lead to future complications that can subsequently lead to death [5].

In this context, technology has been increasingly used to monitor and manage patients with diabetes. These include machine learning models for characterizing glycemic behavior [6], wearable devices for continuously monitoring people with diabetes [7], a handheld health care device for monitoring the diabetic level through the individual's breath [8], the use of infrared light for measuring blood glucose optically [9], the continuous monitoring of glucose levels through multi-sensors [10], the analysis of reliability of clinical diagnoses through the joint use of SVM using statistical modeling Naïve Bayes [11], measuring of glucose concentration in the blood through a microwave sensor [12], self-management and remote monitoring of diabetes through the mobile health platform (mHealth) [13], monitoring glucose through a portable non-invasive device that uses infrared sensors [14], and the prevention of foot ulcers in diabetics through intelligent means (*smart socks*) [15]. Another recent and highly promising technology related to the Internet of Things (IoT) when applied to the health area is the Internet of Health Things (IoHT); this is quite promising as it contributes attention, diagnosis, and faster and more precise treatments [16]–[19]. The measurable benefits of connected medical devices include reduced mortality rates, fewer visits to clinics, reduced emergency and hospital admissions, faster care, and shorter hospital stay [20], [21]. The remote monitoring of patients promotes a more effective and timely treatment and enables the better management of health. Additionally, patients (and their relatives) obtain greater visibility regarding their health conditions, allowing them to play an active role in the control and positively influencing the treatment [22], [23].

In the mid-2000s, the continuous glucose monitor (CGM) appeared in the market with the promise of treating main diabetes problems. For example, the multiple insulin injections and glucose measurement rate punctures or the end of postprandial hyperglycemia and nocturnal hypoglycemia cases. CGM seeks to improve the quality of life for people

with diabetes. All CGM devices have been approved as complementary and alternative and need to be calibrated two to four times a day [24].

During the last years, there has been extensive research in data mining and machine learning applied to diabetes [25]–[27]. Therefore, the development of solutions that facilitate data capture in real time is relevant.

In this work, we present the adaptation of hardware to a portable device based on the IoT architecture and called LibreMonitor, in order to continuously and remotely monitor the condition of diabetic patients. This hardware uses an NFC module together with an IoT card, which captures data from the glucose measurement of the Freestyle Libre sensor and transmits it via Bluetooth LE communication to a mobile application. The application allows the patient to view the screen; thus, they can see their blood glucose rates in real-time and also access their records. The data collected and displayed in the application is transmitted via WiFi/3G/4G communication to a secure cloud-based platform, where healthcare professionals will store and analyze it.

The remainder of this paper is organized as follows. Section II discusses some relevant works in the field. In Section III, we show our proposed solution. The setting and environment are presented in Section IV; subsequently, Section V presents the results and Section 6 presents the conclusions formed and suggestions for future work.

II. RELATED WORK

Nowadays, many devices are available that work with specific methods to monitor diabetic patients [28]. All methods are efficient or sufficient for detecting glucose rates; however, these lack some features such as forecasting real-time data from sensors connected to the patient's body and providing alerts regarding hypo- and hyperglycemia [29]. We reviewed the literature to investigate current prevention and medical recommendation platforms, structures, systems, and applications. The areas of research reviewed included e-Health, health sciences, information technologies, and mobile applications among others.

There are several high-cost blood glucose monitoring tools available on the market, such as Medtronic (Minimed 640G) and Dexcom (Dexcom G4 and G5) continuous monitoring systems. Relatively low cost such as Abbott's flash monitoring (Freestyle Libre) are also available, which displays the glucose rate through a scanner [30].

Proposals for knowledge-based clinical decision support systems have been made to monitor patients with chronic diseases and improve their quality of life. These systems allow patients to record the lifestyle changes they will adopt, and the system uses these preferences to generate personalized recommendations [31]. For example, DialBetics is a smartphone-based self-management support system for patients with type 2 diabetes. DialBetics has four modules: data transmission, evaluation, communication, and food assessment module. Additionally, the system is a partially automated, real-time interactive system that interprets patient

data such as biological information and information related to exercise and dietary content, thereby helping patients achieve self-management of diabetes.

The proposed solutions include evolutionary rule decision-making using similarity-based patients with associative chronic diseases to normalize clinical conditions, using information from each patient and recommending guidelines corresponding to the conditions detailed in the decision-support system’s rule-based inference (CDSS) [32]. The authors improved the conventional rules-based CDSS algorithm to report on the unique characteristics of patients with chronic diseases and preventive strategies and guidelines for complex diseases. Moreover, the proposed evolutionary rule decision-making program selectively uses a range of databases in chronic disease patients. Furthermore, a set of commercially available mobile apps assess their impact on diabetes self-management [33].

Overall, our analysis indicated that mobile applications are viable tools for diabetes self-management and are preferred over web-based or computer-based systems with usability. The review also found that diabetes self-management applications are as useful to patients as providers. In addition, using mobile apps reportedly improved positive health habits such as healthy eating, physical activity, and blood glucose testing.

III. PROPOSED SOLUTION

The poor control of the disease through manual treatments increases the risk of nocturnal hypoglycemia and/or postprandial hyperglycemia [1]. These situations can cause various health problems, such as blindness, amputations, kidney, heart problems and even death. Based on these scenarios, the predominant motivation for the development of this prototype is the improvement of the quality of life of diabetics and their families. For this, we use a flash glucose monitoring sensor (FGM)– Freestyle Free [34]– and integrate it with mobile hardware and software. Thus, our prototype permits monitoring the patient’s glycemic rate, acting as a CGM system and generating alerts and graphics that are stored in the cloud with adequate security and ensuring the privacy of patient data.

This proposal presents the adaptation of static to portable hardware. Integrating different devices thus facilitates the continuous monitoring of patients with diabetes at a low cost.

We present below the high-level architecture of the proposed approach. In Figure 1, it is possible to visualize the integration of the different devices/artifacts used in the proposal.

In Figure 2, we present a scheme of the IoT architecture used in the proposed system.

According to the 3-layer model of the Internet of Things, the perception layer is constituted by different devices (sensors, things). The primary task of this layer is to measure, collect, and process the information (perceive the physical properties of things) to transmit it through the communication

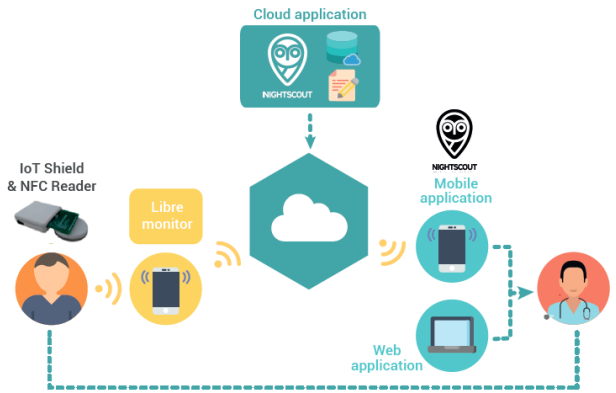


FIGURE 1. Proposed high-level architecture. The integrated communication of the devices from the IoT board, passing through the cloud application, delivers the glucose-related data o the healthcare professional’s device.

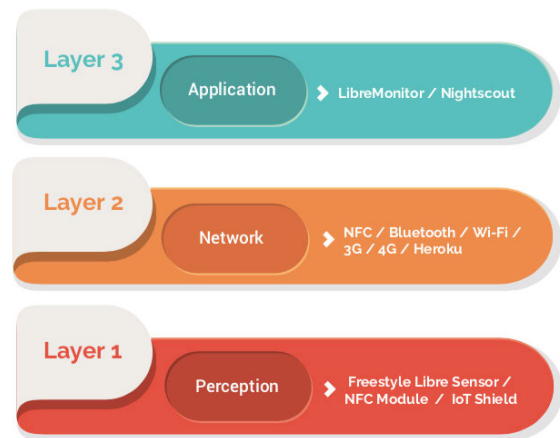


FIGURE 2. 3-Layer IoT proposed architecture.

channels. In this context, we will present the hardware and software parts of this layer.

A. PERCEPTION LAYER

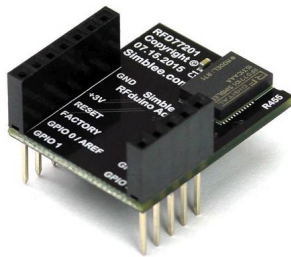
The hardware used for the development of the real-time blood glucose monitoring system was the RFD77201 model board. This hardware uses the microcontroller model RFD77101 from Simblee [35]. This card features embedded Bluetooth LE (Low Energy) technology and the NFC BM-019 module from Solutions Cubed [36]. The development platform used to program the RFD77201 and BM-019 was Arduino IDE, using the embedded C ++ language to program devices to collect (BM-019), handle and send (RFD77201) data to the mobile app.

1) SENSOR FREESTYLE LIBRE

The Freestyle Libre sensor uses a model RF430TAL152H chip manufactured by Texas Instruments. This sensor works with NFC ISO/IEC 15693 and 14-bit Sigma-Delta ADC technology and standard respectively. The RF430TAL152H chip contains 244 blocks of 8 bytes each of non-volatile Ferroelectric Random Access Memory (FRAM), which can

TABLE 1. Comparison of IoT boards.

Board	Communication technology	Dimensions
RFD77201	Bluetooth LE	7 mm x 10 mm x 2,2 mm
Arduino Tian	WiFi	53 mm x 68,5 mm
Arduino 101	Bluetooth LE	68,6 mm x 53,4 mm
DFRobot Bluno	Bluetooth LE	60 mm x 53 mm

**FIGURE 3.** RFD77201 board referenced in Table 1.

be read via NFC using a normal block read command, such as from a cell phone. The FRAM is sorted into sections comprising of multiple blocks, and each block is protected by a CRC-16 in the first two bytes.

2) NFC BM-019 MODULE

The NFC module used to read Freestyle Libre sensor data was the BM-019 from Cubed Solutions. The selection was only determined by the NFC ISO/IEC 15693 standard, which is compatible with the Freestyle Libre sensor.

3) IoT BOARD

The RFD77201 board was selected because it possess features essential for IoT. Features such as small size, integration with the leading mobile operating systems in the market (iOS and Android), and—predominantly— its wireless technology with embedded Bluetooth LE that aids in communication with other devices.

Cards with embedded WiFi and Bluetooth are available on the market. The determining factor for the selection is its size. A big board would lead to a larger prototype and could affect ease of use. Table 1 compares the RFD77201 (Figure 3) board with other boards with embedded wireless technology.

B. NETWORK LAYER

In this Layer, we used the following technologies:

- **NFC:**
NFC communication technology, ISO/IEC 15693 standard, was used to collect the data stored in the Freestyle Libre sensor through the NFC module BM-019.
- **Bluetooth:**
Bluetooth LE wireless technology communicates the Simblee RFD77201 card with the mobile device. The data, once collected by the BM-019 card, is encapsulated and transmitted to the smartphone.
- **Wi-Fi:**
Wi-Fi communication technology, IEEE 802.11× standard, is used to transmit the data to the Internet;

C. APPLICATION LAYER

1) LibreMonitor

LibreMonitor is an open-source application developed and maintained by Uwe Petersen¹ for the sake of research and has no relationship to Abbott. The programming language used to develop the application was Swift 3.0, which is open-source and produced by Apple for the development of its products such as iOS.

LibreMonitor works by checking the Freestyle Libre sensor frequently—for example, every two minutes—and transferring all the 32 history values, glucose rate measurements, glucose rate measurements from the last eight hours, the 16 current time trend values, and the values from the previous 15 minutes. After gathering all the data, it displays the rates in graphical and tabular formats on the smartphone.

2) NIGHTSCOUT

The Nightscout app is a cloud-based, open-source project that allows access and works with CGM data. Nightscout aims to provide users access to real-time glucose data by storing that data in the cloud. Apart from web-based data visualization, Nightscout can also receive data from a smartphone or smartwatch to monitor CGM data of individuals with type 1 diabetes remotely.

The app supports the most common glucose monitoring devices such as Dexcom G5/G4/Share, Medtronic 530g/Veo/Minimed Connect/640g and Freestyle Libre.

Nightscout allows to configure the data securely stored in the cloud. This configuration is undertaken through the administration tools, where the admin can register several type of users (patient, parents, doctors, etc.). Moreover, it allows generating pre-established access models (read-only, administrator, etc.). Additionally, the data provided permits applied machine learning and the application of data-mining techniques.

IV. SETTING ENVIRONMENT

For this study, we will use an FGM sensor, an NFC module, and an IoT board [37], [38]. Below are the steps for developing the FGM sensor glucose rate meter and the mobile app:

- We will define the FGM sensor as Freestyle Libre, which applies to the patient's body and records the blood glucose rate every 15 minutes. Freestyle Libre does not display this information unless manually scanned;
- The NFC module will read the FGM sensor information. The first 43 blocks contain the last 15 minutes and the last 8 hours of glucose measurements.
- The IoT card will encapsulate the data collected by the NFC module and transmit it to the mobile application. The patient will define the collection period. The encapsulated data packet will contain the information collected by the NFC module, its serial identifier, and the board temperature;

¹<https://github.com/UPetersen/LibreMonitor>

- The sensors can be powered by 3.3v lithium battery or via USB;
- The mobile application will be LibreMonitor, developed and provided for this work by Uwe Petersen [35]. The application was written for the iOS platform. The application receives the data via bluetooth from the IoT card. LibreMonitor shows the patient the current glucose rate and the data for the last 15 minutes and the last 8 hours. Also, a graph shows the evolution and glucose trend. Finally, the app also allows calibration. Thus, the information presented is closer to that registered by the FGM sensor.
- The cloud app will be the Nightscout [39]. Nightscout can be accessed through a browser or mobile app (iOS and Android). The app provides the following features: storage of data transmitted by LibreMonitor, secure access to information, dashboard with glucose rates including current rate, reports for patient status monitoring and decision making by doctors and caregivers.

With the device ready and integrated into the cloud and mobile app, we will follow system evaluation with a healthy adult patient using a Freestyle Libre sensor.

Optionally, the sensors (NFC module, IoT board, and LiPo battery) can be integrated into a printed circuit board and mounted in a 3D printed case.

V. RESULTS

A. LibreMonitor EVALUATION

For LibreMonitor evaluation, we considered two measures of Freestyle in a volunteer. These measures were in the morning, afternoon, and evening. Furthermore, compensation calibration was performed, thereby avoiding value disparities between LibreMonitor and Freestyle Libre. Following verification, LibreMonitor transmitted the data to the Nightscout cloud application over WiFi/3G/4G, where it is stored in the database and will be available for future analysis and reporting.

B. LibreMonitor COMPARISON

The comparison of LibreMonitor's results with the Gold Standard (Freestyle Libre) was performed through the reports of the glyceimic averages in the period from 26 to 28/05/2018 and is shown in Figure 4.

In Figure 4, it can be observed that, based on the Freestyle Libre glyceimic average, LibreMonitor reaches the following percentages: 94.60% on May 26; 87.87% on 5/27; and 103.94% on 5/28. These small differences indicate the reliability of LibreMonitor for measurements of diabetic patients, requiring proper sensor calibrations and suggest that the amount of glucose rate captured is equal to that of Freestyle Libre.

C. GRAPHICAL INTERFACE

Initially, the system loads the graphical interface (as shown in Figure 5). The function is to display information related to checks, graphs and historical glucose rates, IoT

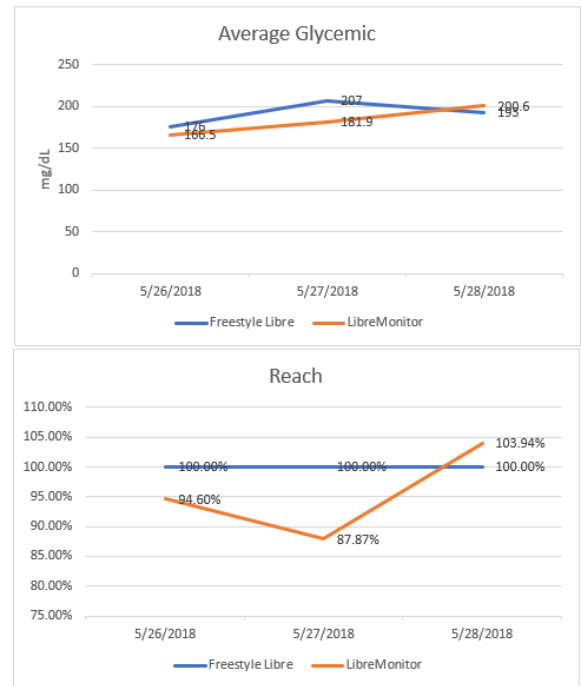


FIGURE 4. Comparison of average glyceimic range from freestyle libre and LibreMonitor.

(Simblee) card status, application calibration (offset and slope), real-time glucose, measurement history, NFC module and sensor ID, ambient temperature, sensor status, current measurement graph, and information from the last 15 minutes and last 8 hours.

The glucose line, highlighted in red in Figure 6, denotes the current glucose rate value and the two delta values show how glucose is about to develop (linear extrapolation over the next fifteen minutes). The first delta value is the difference between the current and previous values, and the delta value is the difference between the current glucose value and twice the glucose value 8 minutes ago. The two prognostic glucose values, or trends, are calculated by adding the delta values to the current glucose value [40], [41].

The glucose rate is calculated from the gross value as shown in Equation 1:

$$g = (ab) + c \tag{1}$$

where:

- g = glucose;
- a = gross values. Captured by the NFC module and sent by the IoT card to the mobile application (converted to application values);
- b = slope. Fixed value, converts gross values to the approximate values measured by the sensor;
- c = offset. To correct the differences in values captured by the sensor with the mobile application. Figure 7 shows the mobile app calibration.

D. SETTINGS INTERFACE

The Settings interface (Figure 8) shows the Calibration and Upload to Nightscout options. These options permit

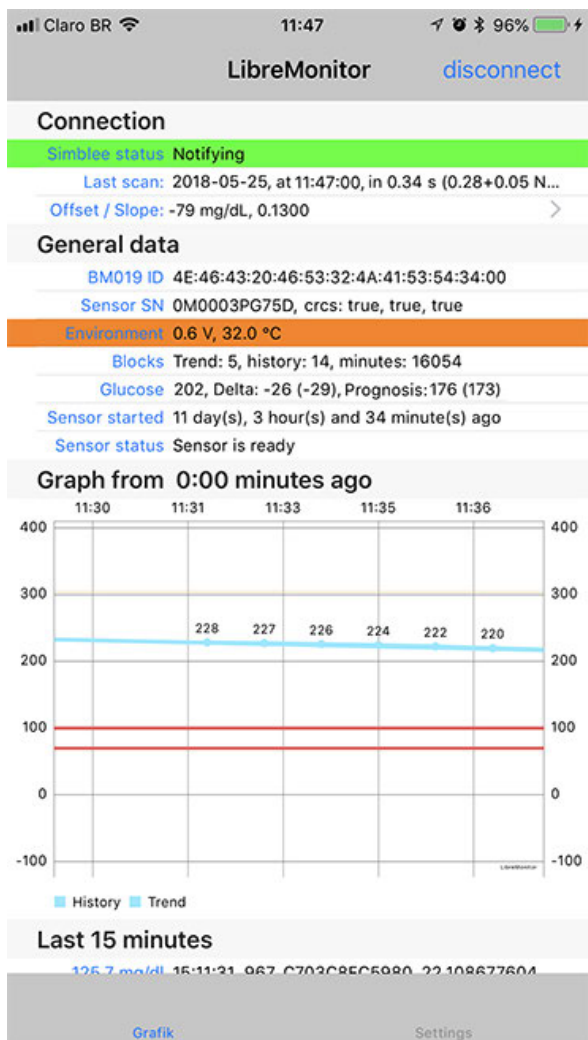


FIGURE 5. LibreMonitor main graphical interface exhibits information regarding the connection, general data and glucose trend/history graphic.

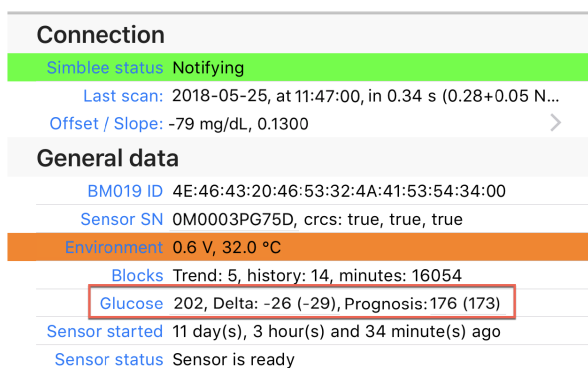


FIGURE 6. Current glucose rate, delta, and prognosis.

configuring the service in the Nightscout cloud. The recorded data will allow the professionals to analyze and report measurements.

E. CLOUD APPLICATION

By accessing the Nightscout cloud application (as shown in Figure 9), the main screen displays information regarding glucose rates over time and hypo- and hyperglycemia alerts.

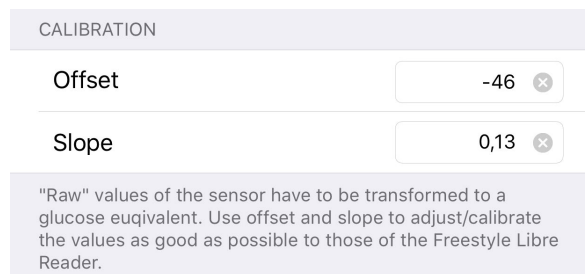


FIGURE 7. Calibration interface.

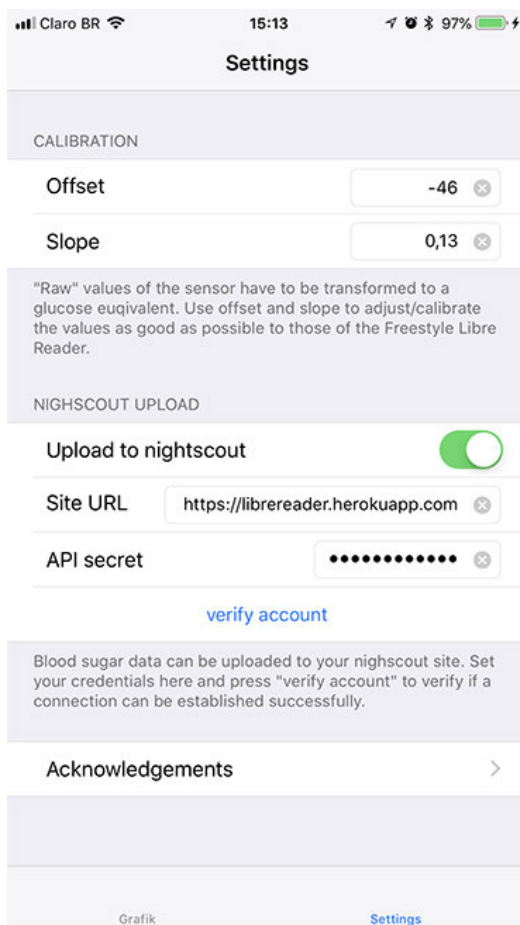


FIGURE 8. Settings interface, which exhibits the options for device calibration and data upload for Nightscout cloud application.

F. HARDWARE MODIFICATION

To perform the system evaluation, we invited a healthy adult as a volunteer; also, we adapted the hardware that reads Freestyle. Figure 10 provides the details of the prototype attached to the volunteer's arm.

G. SYSTEM EVALUATION

For the evaluation of the system, we recorded the measurements at irregular periods. The assessment was performed depending on the availability of the sensor. Due to its high price and low availability, we faced difficulties in the evaluation several times. The cost and availability also influenced the number of volunteers.

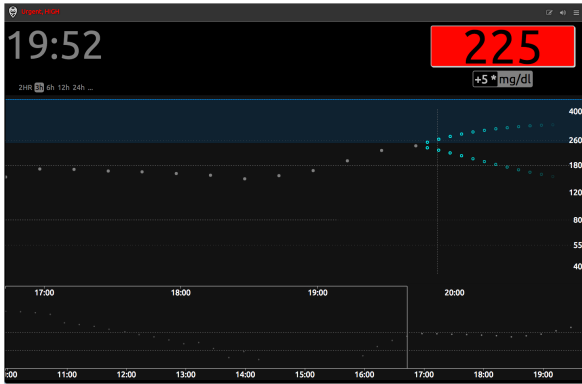


FIGURE 9. Nightscout cloud application interface.

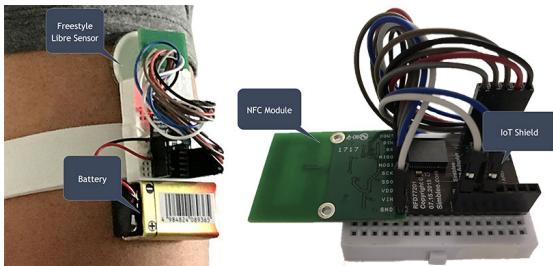


FIGURE 10. Prototype’s hardware modifications that shows the freestyle libre sensor, NFC card, and IoT board.

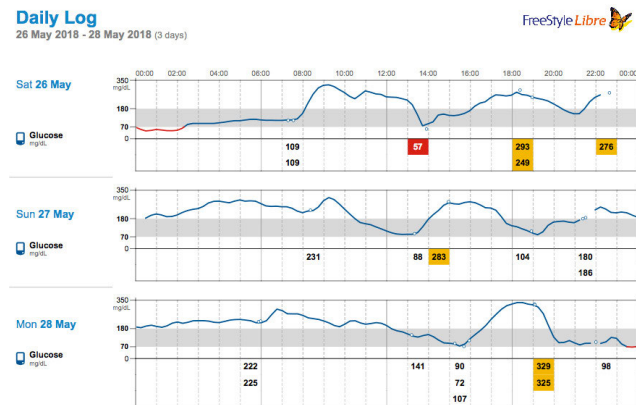


FIGURE 11. Glucose rates from 26 to 28/05 - freestyle libre.

The period selected for the evaluation was May 26–28. During this period, we gathered the largest number of measurements. Following it, gaps can be observed, especially on May 27. The absence of the patient caused differences in the calculation of daily glyceamic averages between the mobile application and Freestyle Libre.

Calibrations were performed only once a day during the initial measurements.

The charts used in this section were generated by Abbott’s official application. The sensor data was exported from the scanner and was stored by the Nightscout and are available for consultation.

Figure 11 shows the patient’s glucose rates, recorded from May 26 to 28, 2008 with Freestyle Libre. The chart

Day to day

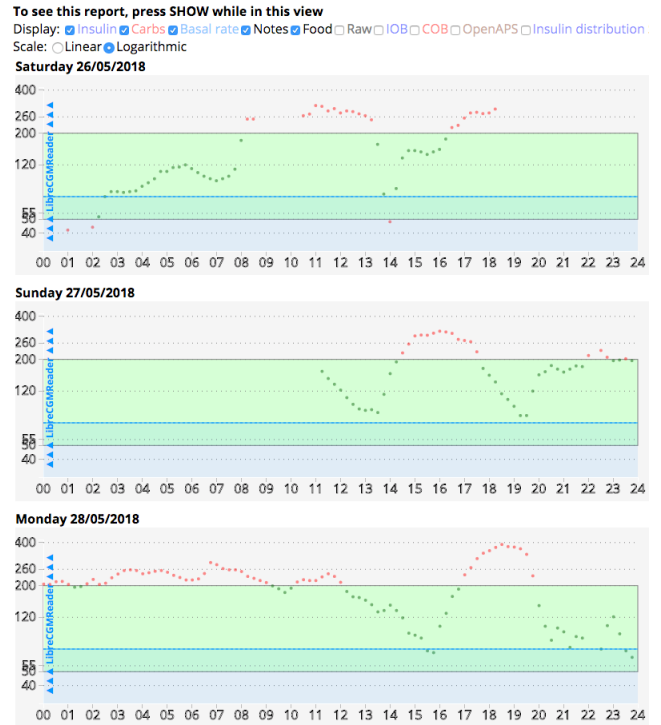


FIGURE 12. Measurement chart from 26 to 28/05 - nightscout.

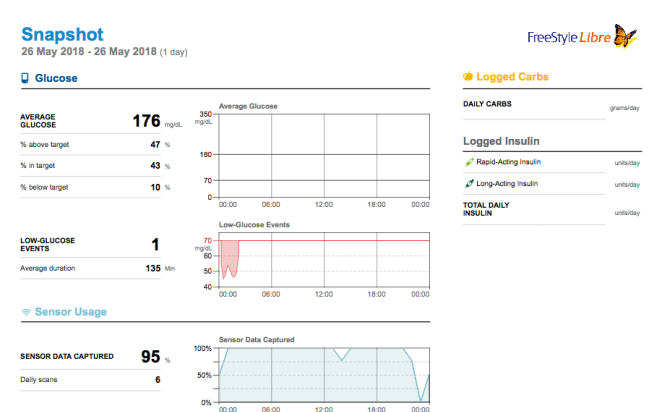


FIGURE 13. Glycemic average May 26 - freestyle libre.

line is generated with measurements taken internally every 15 minutes [36] by the sensor (but is not presented to the patient).

Figure 12 shows the chart provided by the cloud application, which shows glucose rates for the same period. We can see all measurements taken from the FL sensor, including those that the previous chart does not display. A similarity can be observed in the plotting of the charts, where the rates have similar values. Moreover, it can be observed that on May 27, the checks were performed only in the afternoon, which may impact the glyceamic average of that day.

Analyzing the samples from May 26th, 27th, and 28th separately, it can be observed that the glyceamic averages between the data recorded from the mobile app and Freestyle

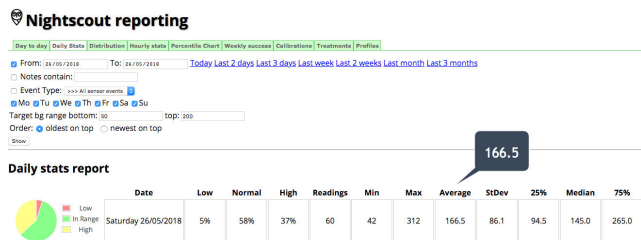


FIGURE 14. Glycemic average May 26 - cloud application.

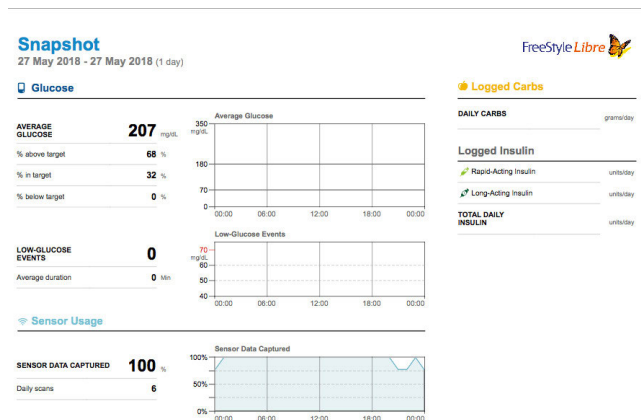


FIGURE 15. Glycemic average May 27 - freestyle libre.

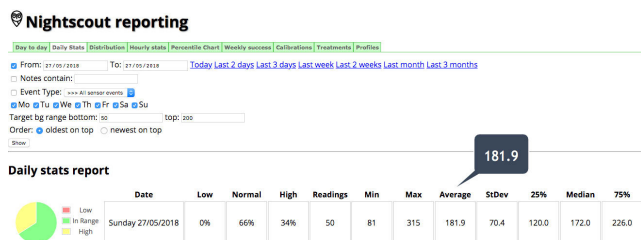


FIGURE 16. Glycemic average May 27 - cloud application.

Libre are highly similar. The importance of calibrating (tilting and shifting) the mobile application before its use is essential. Research indicates that even with a factory-calibrated device—in this case, the Freestyle Libre—there may be differences in the values of blood glucose measurements [36], [42]. Considering this scenario, even with the observed differences, we can recognize the robustness and effectiveness of the proposed system.

Figures 13 and 14 show that the glycemic average on May 26 was 176 mg/dL for Freestyle Libre and 166.5 mg / dL for the mobile app.

We can observe from Figures 15 and 16 the most significant difference in glycemic averages on May 27. The difference may have been caused because the patient did not make calculations with the application in the morning.

For May 28th sampling, the patient was on the system for an entire day. Freestyle Libre presented a glycemic average of 193 mg/dL (Figure 17) and the mobile application of 200.6 mg/dL (Figure 18).

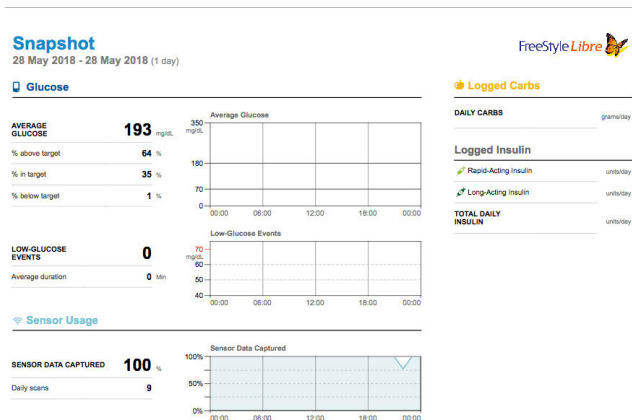


FIGURE 17. Glycemic average May 28 - freestyle libre.

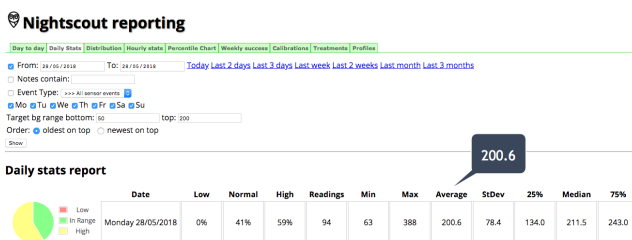


FIGURE 18. Glycemic average May 28 - cloud application.

TABLE 2. Glycemic averages.

Glycemic Average (mg/dL)	Freestyle Libre	LibreMonitor	Difference
May 26	176	166,5	5,40%
May 27	207	181,9	12,13%
May 28	193	200,6	-3,94%

TABLE 3. Price comparison between solutions.

Product	LibreMonitor	BluCon	Miao Miao
Price (USD)	75,00	110,00-165,00	199,00

The percentage difference in the glycemic averages between the system and Freestyle are shown in Table 2.

Even though the system was tested on only one volunteer, it had positive and negative points and possibilities for improvement.

1) POSITIVE ASPECTS

Accurate, easy to read, graphical and reportable analysis with clear real-time accuracy, and hypo- and hyperglycemia alerts. Although the hardware acquisition cost is high, it is still helpful to invest in LibreMonitor over market devices (ex. BluCon by Ambrosia Systems Inc. [40] and Miao Miao by High Brilliant Technology [41]). We can compare the price of the presented alternatives in Table 3; furthermore, the last two are not sold in part of South America.

2) WEAK ASPECTS

The size of the device is not practical because it must be adapted to the patient's body. The LibreMonitor mobile

app only supports the Apple platform. The low number of volunteers was a factor that impacted the evaluations. It was difficult to locate people who use Freestyle Libre, probably either due to lack of information or financial issues since as the product is relatively expensive.

3) POSSIBILITIES FOR IMPROVEMENTS

Migrate to the Android platform, minimize hardware for using with more comfort, and more configuration options such as bolus calculation, patient data, and screen login.

VI. CONCLUSION AND FUTURE WORK

In recent years, data mining, machine learning, and the integration with IoT have emerged as some critical challenges in the health area [19], [25].

In this work, a device capable of converting a flash glucose monitoring-system to a low-cost continuous glucose monitoring system (CGM) was tested. The proposed system can collect Freestyle Libre sensor glucose rate measurements and display them on a smartphone, without scanning manually. A cloud-based application was used to store data and analyze and report the glucose rates for diabetic patients. Furthermore, the data provided allows the application of data mining and machine learning techniques.

Moreover, we tested the glycemic system, comparing it with the Freestyle Libre and gathering a favorable result through few differences observed in the percentages.

We concluded that the system meets the criteria of glycemic average, precision, and accuracy in the recording of blood glucose measurements made by the sensor and that its use is possible, always with the supervision of a specialized professional.

For future work, we expect that the mobile app can be ported to other platforms and new options can be implemented.

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JOSÉ JORGE RODRIGUES BARATA received the bachelor's degree in information systems from Faculties Nordeste (FANOR) and the master's degree in applied informatics from the University of Fortaleza (UNIFOR). He is currently an Independent Infrastructure Consultant and a Professor. He has served as an Academic Professor of the computer networks course with Ateneu College-FATE and a Scientific Researcher with IEPRO-Institute of Studies, Research, and Projects at UECE. He also acted as an Infrastructure Consultant, a Technical Writer, and an Information Technology Instructor, focusing on consulting and training services for companies and professionals. His research interests include health and wellness technologies, sensor networks and the IoT, mobile and ubiquitous computing. His technical specialities include operating systems (client and server), network infrastructure, information security, and virtualization. He is also a Speaker, Writer, and a Contributor, participating in the publication of technical articles and communities in Brazil regarding Microsoft technology. He has also volunteered in computer science education for students. He has received several internationally recognized technical certifications from Microsoft, CompTIA, Dell, and Exin.



ROBERTO MUNOZ (M'17) received the master's degree in computer engineering, engineering science, and education and the Ph.D. degree in computer engineering. He is currently an Associate Professor with the School of Informatics Engineering, a Principal Researcher with the Research and Development Center in Healthcare Engineering (CINGS), and an Adjunct Researcher with the Center of Cognition and Language (CIDCL), Universidad de Valparaíso. He has authored over 80 scientific articles. His research interests include computers and education, multimodal learning analytics, human-computer interaction, and health informatics. He is also a TPC Member in refereed international conferences and highly reputed journals. He is currently an Editor of the *International Journal on Computational Thinking (IJCThink)*.



RAFAEL D. DE CARVALHO SILVA received the graduate degree in mathematics from the Institute of Education, Science, and Technology of Ceará (IFCE), in 2012, and the master's degree in applied informatics from the University of Fortaleza (UNIFOR), in 2016, where he is currently pursuing the Ph.D. degree in applied informatics. He is currently a Researcher with the Industrial Informatics, Electronics, and Health Research Group. He has experience in the areas of computer graphics, motion capture, 2D and 3D animation, and digital game creation.



JOEL J. P. C. RODRIGUES (S'01–M'06–SM'06) is currently a Professor with the Federal University of Piauí, Brazil, and a Senior Researcher with the Instituto de Telecomunicações, Portugal. He is also the Leader of the Internet of Things Research Group (CNPq), a Director of the Conference Development-IEEE ComSoc Board of Governors, an IEEE Distinguished Lecturer, the Technical Activities Committee Chair of the IEEE ComSoc Latin America Region Board, and the Past Chair of the IEEE ComSoc e-Health and Communications Software TCs. He has authored or coauthored over 780 publications in refereed international journals and conferences, three books, two patents, and one ITU-T Recommendation. He is also the Editor-in-Chief of the *International Journal of E-Health and Medical Communications*.



VICTOR HUGO C. DE ALBUQUERQUE (M'17–SM'19) received the graduated degree in mechatronics engineering from the Federal Center of Technological Education of Ceará, the M.Sc. degree in teleinformatics engineering from the Federal University of Ceará, and the Ph.D. degree in mechanical engineering from the Federal University of Paraíba. He is currently a Professor and a Senior Researcher with the University of Fortaleza, UNIFOR, Brazil. He is also working as an Assistant VI Professor with the Graduate Program in Applied Informatics, UNIFOR, and the Leader of the Industrial Informatics, Electronics, and Health Research Group (CNPq). He is also a Specialist mainly in the IoT, Machine/deep learning, pattern recognition, and robotic.

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