Original Article

Prediction of Type-2 Diabetes Level with the Smart Sensor System

Mohammad Husain[1], **Arshad Ali**[2]

[1, 2] Faculty of Computer and Information Systems, Islamic University of Madinah, Kingdom of Saudi Arabia.
Email: [1] dr.husain@iu.edu.sa, [2] a.ali@iu.edu.sa

***Corresponding Author:** Mohammad Husain

Faculty of Computer and Information Systems, Islamic University of Madinah, Kingdom of Saudi Arabia.
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Abstract

There are a number of type-2 diabetes mellitus models available that can be used in different ways, including estimating long-term clinical outcomes, estimating the costs of clinical trials, as well as assisting in making decisions to determine which interventions are best suited for these populations. The current research aims to present an algorithm for mobile or smart sensor systems to predict the blood glucose level in type 2 diabetic patients.

Dexcom system was considered as a study tool. The efficiency of a revised Dexcom system with an advanced algorithm was assessed. The prediction of future glucose concentration is predicted by using suitable modeling approaches.

The accuracy and dependability of the Dexcom system can be considerably enhanced by using advanced denoising and calibration algorithms. The precision and consistency of the continuous glucose monitor improved over time, with the greatest improvement. According to the findings, signal-processing-induced time delays have been decreased, and performance at low plasma glucose has been enhanced. Advances in sensor systems' performance are expected as a result of these enhancements.

This application effectively maintains a stable blood glucose level because blood glucose level reaction times are delayed when glucose is consumed. Furthermore, the findings of this work can be used to improve closed-loop systems and provide information to insulin pumps.

Keywords: Type-2 diabetes, Dexcom system, Blood glucose level, Mobile sensor system, Hyperglycemia.

INTRODUCTION

Diabetes mellitus, often recognized as diabetes, is a disease that disturbs the hormone insulin, causing improper glucose metabolism and higher blood sugar levels. High blood sugar affects a variety of organs in the human body, complicating a number of physiological functions, including the blood vessels and neurons. Although the exact origins of diabetes have yet to be determined, numerous scientists believe that both inherited and ecological factors have a role. In any event, people with diabetes are more common in adults, so it is referred to as "adult-onset" diabetes. Diabetes mellitus is now thought to play a significant role in ageing.

According to the International Diabetes Federation, the number of people with diabetes mellitus reached 382 million in 2013[1], accounting for 6.6 % of the global adult population. As per the world healthcare medical statistics, the diabetic disease is anticipated to rise from 376 billion to 490 billion by 2030[2].

Furthermore, diabetes may be an individual causative risk factor for microvascular entanglement. Diabetic patients are likely to be more impotent in the face of a higher risk of microvascular damage, and as a result, persisting difficulties of cardiovascular disease are the primary cause of death. Retinopathy, nephropathy, and neuropathy are all symptoms of microvascular damage and rapid cardiac vascular disease [3].

Patients used to check their blood glucose level (BGL) 3-8 times a day using a finger needle to regulate their insulin levels based on their carbohydrate consumption. The evolution of Continuous Glucose Monitoring (CGM) systems has developed considerably, resulting in a wide range of devices on the general market [4]. A Continuous Glucose Monitoring system typically consists of a sensor applied to the skin and a reader that displays the blood glucose level curve. Because blood glucose level reaction times are delayed in relation to glucose consumption, understanding how the blood glucose level of the human body will develop is critical for diabetes patients to avoid hypo or hyper occurrences. As a result, they may be able to maintain a blood glucose level that is not detrimental to the body, reducing the immediate and long-term impacts of diabetes.

Figure-1

Bunescu et al. [5] established a strategy for applying physiological models to predict blood sugar levels in individual patients. These models needed up to seven distinct input features to achieve reliable predictions. Furthermore, they did not discuss the applicability of their technique to mobile devices in their study. Support Vector Regression was found to be suitable for the prediction of blood glucose levels after more research on this subject [5-8].

Those techniques lack an inconspicuous mobile device that does not demand the user's active involvement and provides an alert if specified blood glucose levels are exceeded. Breton et al. [9] presented a different technique. They created a closed-loop system that eliminates the need for users to inject themselves with insulin.

Figure-2

This system, which consists of a glucose monitoring device and an insulin pump, is designed to manage the glucose balance in the body on its own throughout the night. Diabetic clinical instruments provide objective values for result measurement with a degree of reliability and validity. However, because this device was designed for type1 diabetes patients who require regular insulin injections, it is not suitable for individuals with type2 diabetes who do not need an insulin pump. Hence, all of the above papers tried to predict blood glucose levels accurately but were confined to requiring a physiological model and lacked a subtle, mobile application.

The current research aims to address this gap by presenting an algorithm for mobile or smart sensor systems to predict the blood glucose level in type2 diabetic patients.

LITERATURE REVIEW

Diabetes has two primary forms, insulin-dependent diabetes mellitus and non-insulin-dependent diabetes, of which type2 diabetes is the most common [10]. The dysfunction of type2 diabetes impacts how your body processes glucose (sugar), but it also affects how it stores and processes other types of energy, such as fat. A hormone called insulin takes sugar into the cells to function normally. When insulin is not produced enough or our bodies stop responding appropriately to insulin, sugar builds up in our blood. People with diabetes develop this problem.

When untreated, hyperglycaemia can cause serious problem [8, 11]

Chronic metabolic diseases such as diabetes can cause cardiovascular disease, arteriosclerosis, hypertension, neuropathy, nephropathy, and diabetic retinopathy. Type2 diabetes occurs most commonly after the age of 40, accounting for about 90% of patients with diabetes [12]. Due to insufficient insulin secretion and insulin action, it results in chronic hyperglycaemia and impaired carbohydrate, lipid, and protein metabolism [13].

To decrease the health burden of diabetes, prevention and treatment are of the utmost importance for health care. The Global Burden of Disease Study found that population growth and aging increased the number of people with diabetes and their disability-adjusted life-years [14]. During these instances, disease decision models can support decision-making to determine the long-term economic and health implications of interventions in both the public sector and private sector [15, 16, 17]. The objective of disease decision models is to synthesize both the available data and the existing physiologic relationships into coherent models that can be extended in the future.

There are a number of type2 diabetes mellitus models available that can be used in different ways, including estimating long-term clinical outcomes, estimating the costs of clinical trials, and assisting in making decisions to determine which interventions are best suited for these populations [18, 19, 20, 21].

Daphne SL Gardner and E Shyong Tai [22] have suggested several genetic and clinical conditions associated with MODY. Diagnosing these conditions remains a challenging task for physicians. However, in most cases, ignorance of the condition has significant consequences for the individual. The underlying genetic causes of diabetes can be targeted for individual care, and the natural history of the disease can be determined. Understanding these infrequent origins of diabetes, using further experimental evidence, and utilizing other biomarkers will positively lead to improved detection rates, which will allow the afflicted person and their family to receive appropriate care and advice.

N Waugh et al. [23] have presented and reviewed only those models that included screening. This new modelling extended an existing diabetes treatment model by adding the screening component. The NSC has a set of criteria when evaluating new proposals for screening. The screening criteria addressed the condition, the screening test/tests, treatment, and the screening program. Diabetes screening was measured using these criteria's.

There are a few reasons to detect lesser degrees of glucose intolerance, such as ICT, partially because this can reduce the risk of cardiovascular diseases (CVDs) by reducing cholesterol level and blood pressure, and partly by preventing some diabetes. Since it is a better option for reducing CVD, principally through statin use and the increasing prevalence of obesity and type-2 diabetes, there is probably a stronger case for screening for undiagnosed diabetes.

METHODOLOGY

Glucose Monitoring and Prediction Technique

A spatial phenomenon Z is assumed to be represented by its realisations $Z(t_1)$, $Z(t_2)$,..., $Z(t_n)$ at time $t_1, t_2,..., t_n$ in traditional Kriging [24]. Then, at time t_0, the Kriging interpolation of Z is shown below.

$$\hat{Z}(t_0) = \sum_{i=1}^{n} \left(\lambda_i Z(t_i) \right),$$

A spatial phenomenon Z is assumed to be represented by its realisations $Z(t_1)$, $Z(t_2)$,..., Z (tn) at time $t_1, t_2,..., t_n$ in traditional Kriging [24]. Then, at time t_0, the Kriging interpolation of Z is shown below. where λ_i is the number of weights that satisfy the normalisation requirement, i.e., (i=1) n (i) =1, and the estimated error is $E[\hat{Z}(t_0) - Z(t_0)] = 0$. The following set of linear equations, as stated in, can be used to derive optimal weights λ_i in Kriging interpolation [24]. As stated by Curran and Atkinson, the following set of linear equations can be used to derive optimal weights I for the Kriging interpolator [25].

$\Lambda = A^{-1} B$,

$$\begin{pmatrix} \lambda_1 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \lambda_n \end{pmatrix} = \begin{pmatrix} \gamma(t_1, t1) \ldots\ldots\ldots \gamma(t_1, t_n) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \gamma(t_n, t_1) \ldots\ldots\ldots \gamma(t_n, t_n) \end{pmatrix}^{-1} \begin{pmatrix} \gamma(t_1, t^*) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \gamma(t_n, t^*) \end{pmatrix}$$

Where Λ is the spatial correlation matrix of the sample with time differences t_1, t_2,..., t_n, and b is a vector whose elements indicate the spatial correlation between t0 and each t_i t_1, t_2,..., t_n. According to Umer, M., Kulik, L., and Tanin, E., all correlations are based on a suitable variogram model specified for the spatial phenomena under observation (2010) [26]. The Mean Square Error (MSE) is derived using real-time data to enhance Blood Glucose level prediction [35]. The block diagram below depicts the suggested prediction approach for glucose prediction using measured data from a sensor implanted in the patient's body. Sensor first collects data and feeds it to the sensing application. The information is saved in a database and combined with the previously collected information. The measured data is utilized to provide a 5/60-minute projection ahead of time. The suggested approach is initially taught, and the prediction error is more significant, but with many historical data values, the prediction is highly near the patient's measured glucose level.

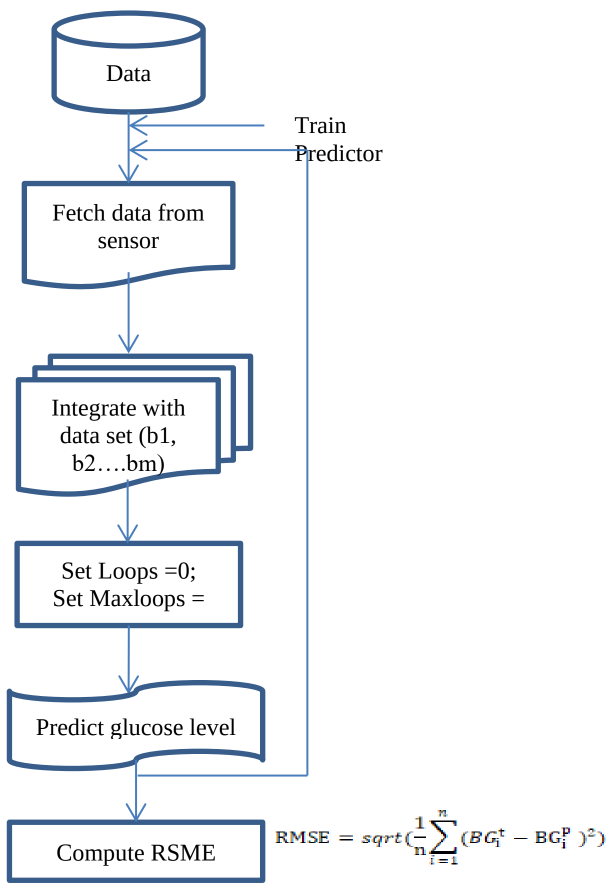

Figure-3. Block diagram of suggested prediction approach

The following equation is used to compute the root mean square error of the given prediction strategy.

$$\text{RMSE} = sqrt\left(\frac{1}{n}\sum_{i=1}^{n}(BG_i^t - \text{BG}_i^p)^2\right)$$

The present estimated Blood Glucose level is BG_i^p The real Blood Glucose level is BG_i^t , and n is the number of anticipated values each day.

EXPERIMENTAL RESULTS

Figure-1 and Figure-2 represents the diabetic monitor that predict the blood glucose level. Figure 5a-5f highlights the results of blood glucose level prediction every 60 minutes. Compared to prediction after 5 minutes in Figure-4a and 4b, prediction accuracy after 60 minutes is more accurate, as represented by figure-5.

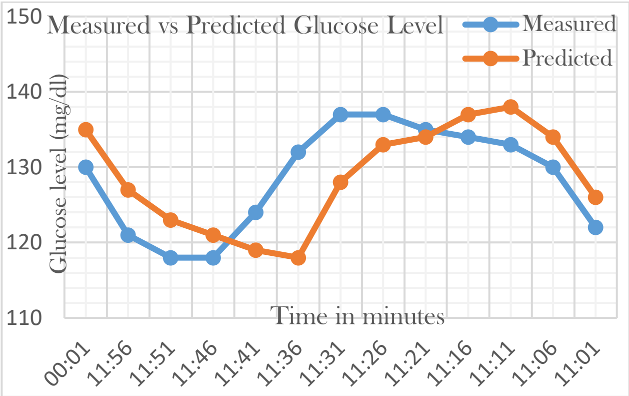

Figure-4(a)

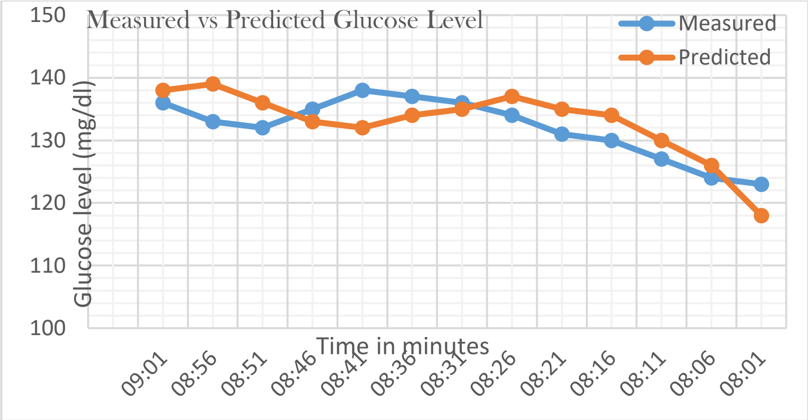

Figure-4(b)

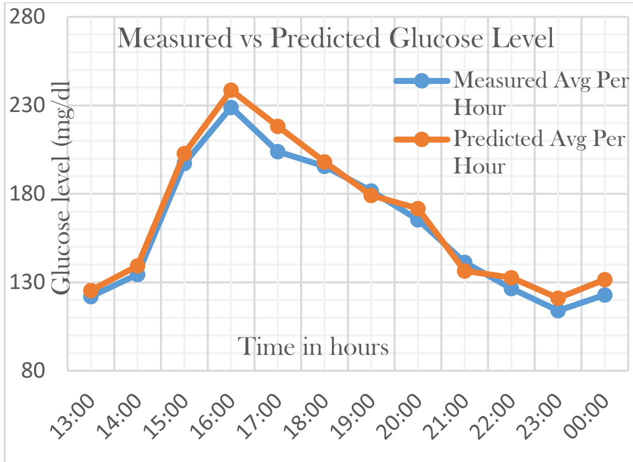

Figure-5(a)

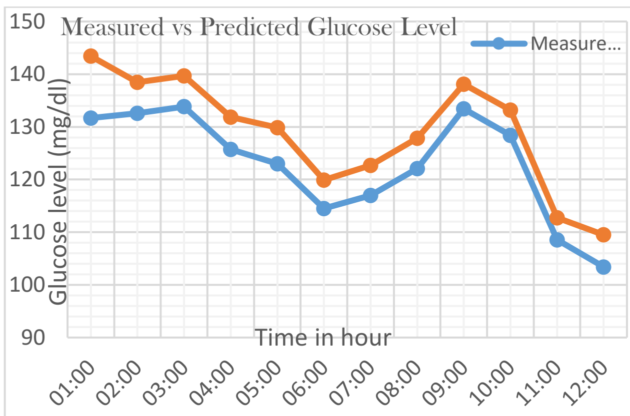

Figure-5(b)

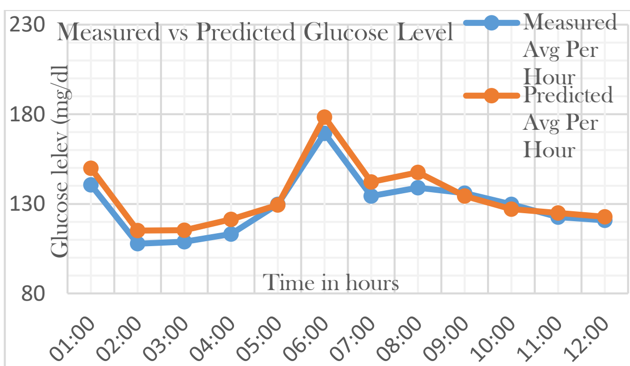

Figure-5(c)

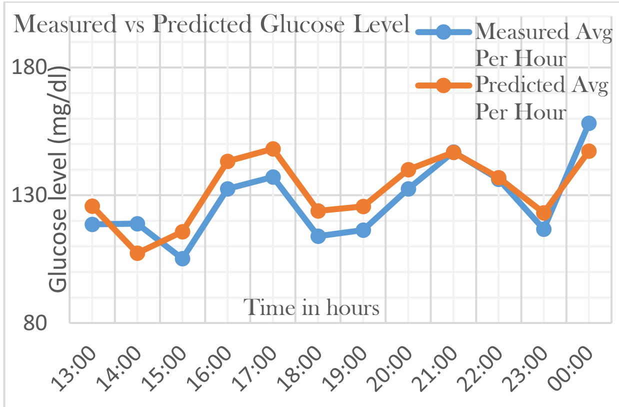

Figure-5(d)

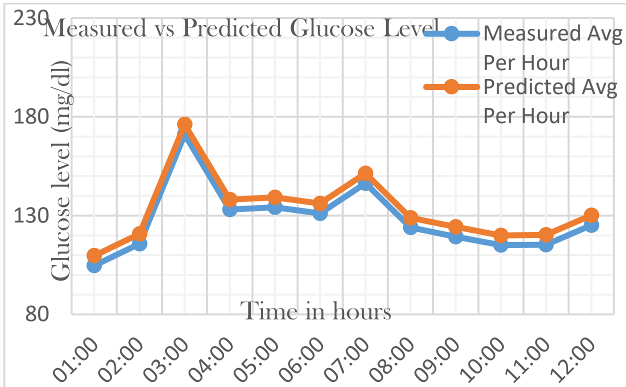

Figure-5(e)

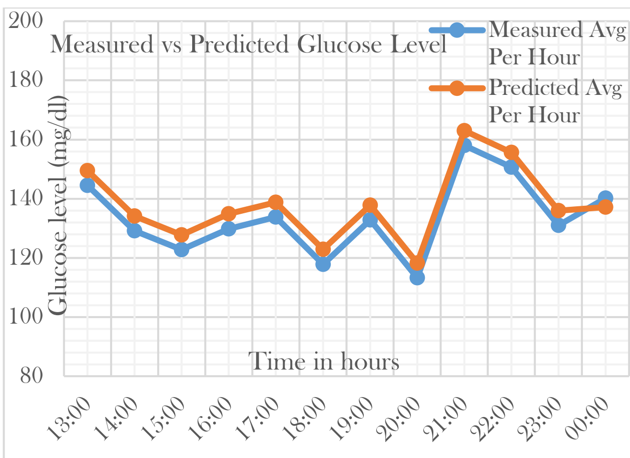

Figure-5(f)

Now the study will assess the efficiency of a modified Dexcom system with an innovative algorithm. The Tandem T-slim insulin pump is compatible with the Dexcom RT-CGM system. Dexcom is also in the process of forming a partnership with Omni Pod. It contains an always-on hypoglycaemia safety alarm that notifies the patient when glucose levels hit 55 mg/dL. When glucose levels drop below or climb above user-selected limits, or when glucose levels rise or fall abruptly, customizable notifications with various tones can warn the user (Figure-6a). The sensor with a connected transmitter can be worn when bathing or swimming because it is water-resistant for up to 8 feet deep for 24 hours.

The Dexcom system is well-suited with the Dexcom share program. The Dexcom Share program delivers real-time glucose data to the cloud, allowing up to 5 caregivers to view real-time glucose readings on Apple or specific Android devices using the Dexcom phone app. Adults and children aged two and up are permitted to utilize it. The Dexcom G4/G5 system needs two blood glucose corrections each day, while the Dexcom G6 is factory certified and therefore does not need any blood glucose measurement. The FDA has certified the Dexcom G6 CGM and the Basal-IQ, which communicate with the Tandem T-slim X2 pump (via low glucose suspend algorithm) to prevent hypoglycaemia when sensor glucose is projected to be less than 80 mg/dL within 30 minutes and resumes when the sensor glucose rises.

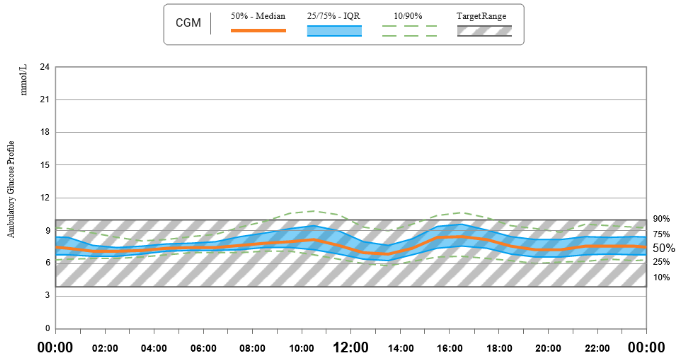

Figure-6(a)

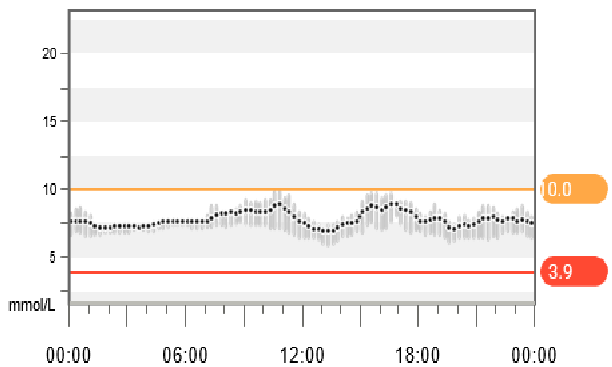

Figure-6(b)

The software used to download CGM data varies with each CGM. A single-page ambulatory glucose profile is a standardized report (Figure-6b). It offers summary information as well as a graph of the glucose profile. The methods for examining CGM data are universal and can be used with any CGM on the market. The first step is to figure out what's going on with your blood glucose levels. Identify and correct any hypoglycaemia episodes that occur. Reviewing the CGM data can help you figure out how long your blood glucose has been in the target range, whether you've had any hyperglycemic or hyperglycemic episodes, and whether you've had any postprandial hyper- or hypoglycaemia [27]. The standard deviation and coefficient of variation are used to analyze blood glucose variability. The better the glucose management, the lower the standard deviation and coefficient of variation are. The error was calculated between measured and predicted by using the proposed algorithm (Figure-7a) and it is showing very promising results as the error is ±5 mg/dl which is considered very good in terms of prediction. The root mean square error between measured and predicted glucose level. The graphs show the error rate calculated hourly (Figure-7b) based and it is maximum 7 mg/dl error rate which is considered very promising in terms of prediction of glucose.

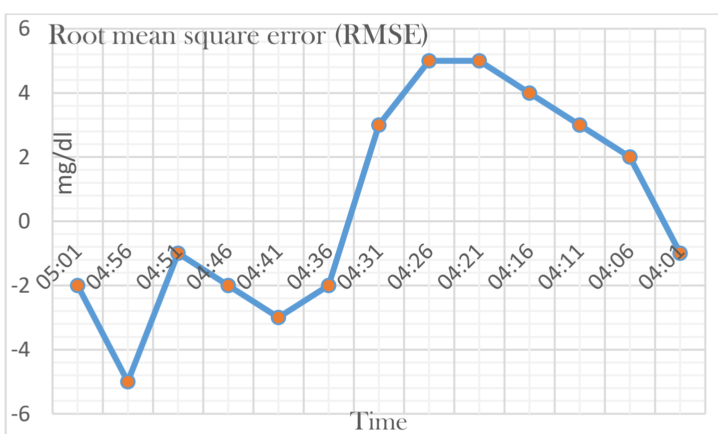

Figure-7(a)

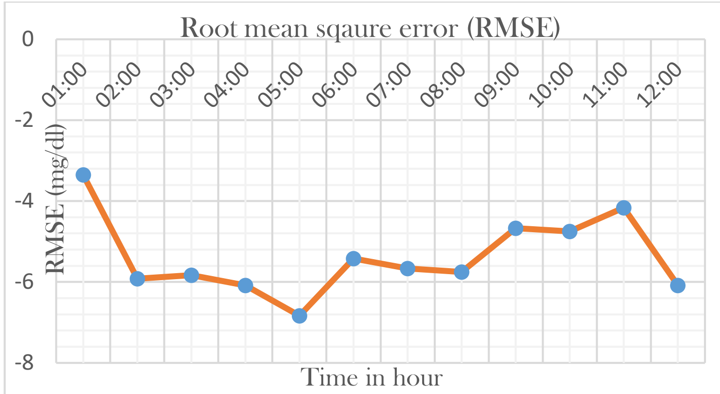

Figure-7(b)

The accuracy and dependability of the Dexcom system can be considerably enhanced by using advanced denoising and calibration algorithms. The accuracy and consistency of the continuous glucose monitor improved over time, with the greatest improvement. According to the findings, signal-processing-induced time delays have been decreased, and performance at low plasma glucose has been enhanced. Improvements in sensor systems' performance are expected due to these enhancements.

DISCUSSION

This research supports Garcia et al. [28] simulation findings that showed a noteworthy development in CGM performance due to algorithm changes. CGM patients should see a meaningful value from these enhancements. While the location and pace of glucose change are vital to patients' diabetes treatment, the CGM's level reliability is essential to the patient's CGM satisfaction [29, 30]. A person will be less inclined to use the CGM data and will be less inclined to stick with CGM if the CGM and predicted glucose are not in agreement [31]. The precision of this system, which uses twice-daily calibrations, is far superior to any previously available system, and it is the first to have a mean ARD of less than 10%. The Dexcom G4 Platinum has a mean ARD of 13.3 %, the Medtronic 530 G has a 14.9% ARD with Enlite sensor calibrating every 12 hours, and the Enlite sensor calibrates 3-4 times a day has a 14.0 % ARD [32]. Indeed, the point accuracy revealed in this research now outperforms that of certain contemporary blood glucose monitoring systems [33].

Higher true alerts and hypoglycaemia detection rates are aided by the new system's performance in the hypoglycaemia range and minimum lag time. The low number of false-positive alerts should assist users in avoiding alert fatigue, while the high rate of true positive and true negative signals should boost their trust in their CGM [34]. More research is needed to see if this correlates to improved results, including a decrease in severe hypoglycaemia.

The system was determined to be reliable, with consistent performance throughout the course of several days of use. The accuracy of the device did not alter much depending on whether it was used during the day or at night. The majority of users should have a pleasant experience with the system, given only a few people in our sample reported poor sensor performance. The necessity of an algorithm for CGM performance is highlighted in this study. This system's algorithm, which was created between an academic center and industry, improved CGM performance. The G4AP's advances in CGM accuracy and reliability may assist deliver more consistent and precise data input to controllers, allowing clinical and commercial adoption to move more quickly.

Diabetic patients mostly use CGM systems to continuously monitor their glucose levels in real-time, which is currently highly expensive. The CGM device generates hypoglycemic and hyperglycemic alarms, and the patient responds by taking an insulin dose to maintain blood glucose levels. The suggested prediction algorithm for blood glucose monitoring can be extremely useful in an emergency since it can continuously monitor blood glucose levels using prediction. Although the above findings from applying optimal based prediction algorithms are quite promising, certain elements still need to be investigated further in the future. Finally, the prediction module allows users to predict hypoglycemic and hyperglycemic occurrences up to 30 minutes ahead of time.

CONCLUSIONS

This research can serve as a platform for future development. Patients who have had diabetes for a long time become sensitive to the impact that low blood sugar has on their bodies. This can result in an unanticipated shift in consciousness. Because this software can detect hypo and hyper periods even before the reduction or increase in blood glucose level has fully started, it can help to prevent hypo and hyper periods. This application is effective in maintaining a stable blood glucose level because blood glucose level reaction times are delayed when glucose is consumed. The next stage is to test this application with real-time continuous glucose monitoring data and improve the algorithm. Furthermore, the ideal use case would be a single app that supports all available sensors. Moreover, the findings of this work can be used to improve closed-loop systems and provide information to insulin pumps.

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