Analysis and Design Process for Predicting and Controlling Blood Glucose in Type 1 Diabetic Patients: A Requirements Engineering Approach

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ABSTRACT

Engineering smart software that can monitor, predict, and control blood glucose is critical to improving patients' quality of treatments with type 1 diabetic mellitus (T1DM). However, ensuring a reasonable glycemic level in diabetic patients is quite challenging, as many methods do not adequately capture the complexities involved in glycemic control. This problem introduces a new level of complexity and uncertainty to the patient's psychological state, thereby making this problem nonlinear and unobservable. In this paper, the authors formulated a mathematical model using carbohydrate counting, insulin requirements, and the Harris-Benedict energy equations to establish the framework for predicting and controlling blood glucose level regulation in T1DM. They implemented the framework and evaluated its performance using root mean square error (RMSE) and mean absolute error (MAE) on a case study. The framework had less error rate in terms of RMSE and MAE, which indicates a better fit with reasonable accuracy.

KEYWORDS

Blood Glucose, Diabetes, Prediction, Requirements Engineering, Smartphone, T1DM

INTRODUCTION

In recent decades, the impact of data science and communication technology in several domains—particularly the healthcare domain—has been profound to an unprecedented level (Chen *et al.*, 2016). Among the several data sciences and communication innovations, software plays a vital role that requires proper analysis and design process (Carroll & Richardson, 2016). A good example central to data science is how persistent illnesses and chronic diseases in healthcare are managed. Notably,

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data-driven calculations can be made with technology's support to improve healthcare delivery (Chen *et al.*, 2016) and quality of care for patients (Gambo and Soriyan, 2017). This technology assists with monitoring, diagnosis, and smart systems (Jovanov *et al.*, 2005; Bossen *et al.*, 2015; Chen *et al.*, 2016; Pramanik *et al.*, 2017; Gambo *et al.*, 2020). However, these systems are critical because they involve patients living on a large and continued scale. As a result, they are susceptible to mistakes even more if they come from the requirements engineering (RE) process (Bjørner, 2009; Katina *et al.*, 2014; Liu *et al.*, 2016).

Therefore, engineering such a smart software to automatically monitor, diagnose, and predict the blood glucose (BG) levels of patients with T1DM necessitates an appropriate method of RE. In the literature, RE is a recognized phase in the software project lifecycle for determining the quality and success of software-based solutions (Arif *et al.*, 2010; Alshazly *et al.*, 2014; Gambo *et al.*, 2014; Teixeira *et al.*, 2014). Unfortunately, failure in most software-based solutions installed in embedded systems like the Implantable Medical Devices (IMDs) and other hardware-related systems used to control, monitor, and predict continuous BG is due to a lack of a good RE process (Zave, 1982; Rahman, 2014). Deficiency in most of these systems could lead to death in the healthcare domain and other environmental systems connected to life. It is noteworthy to say that when the patient's need is not adequately met and the features of the IMDs are not correctly captured, analyzed, and designed, the system's functionality will not be trusted and reliable (Fricker *et al.*, 2015).

Moreover, the present emergency hospitals use various smart devices for different medical applications, including the patient's monitoring, analysis, treatment, and therapeutic care, such as surgical robots used for operations. Still, the opportunities for utilizing these smart devices in the healthcare field include introducing software components (Sanislav *et al.*, 2012). The software assumes a significant role in therapeutic devices (Pashkov *et al.*, 2016), and software engineering serves as a critical competency for building these kinds of medical device systems (Nessi, 2014). Crucial in smart engineering systems that engender healthcare delivery quality is an appropriate software engineering method. Besides, requirements development is one of the most challenging components of engineering software-intensive systems of high quality (Chung *et al.*, 2012). In most engineering techniques, a great deal of effort is on the functional and non-functional targets of a system. For instance, software specialists often design a product from a set of preferred functional and non-functional objectives primarily based on their perception of the system, resulting in an end product that does not meet supposed end-users needs (Kissoon *et al.*, 2019).

Significant research is currently being directed on smart engineering systems to help patients treat chronic diseases; examples include: diabetes, asthma, and heart diseases (Jovanov *et al.*, 2005). These smart devices can collect vital information about the patient's health and monitor body functions such as pulse, BG level, blood pressure, galvanic skin responses, temperature, body fat, and send specific feedbacks to medical experts (Chan *et al.*, 2012). These systems are used to treat, predict, prevent, and manage disease (Klonoff *et al.*, 2017). This justifies the need to understand further the patient's physiological state, the kind of meals they take, exercises, and other events to develop adaptive control systems that can deliver personalized treatments for patients with diabetes (Gao *et al.*, 2017).

Despite the significant progress made in the control of diabetes, there is still a need to engineer a system through proper analysis and design process that can provide the best solution in monitoring and predicting the BG levels of patients with T1DM. Remarkably, diabetes requires regular self-monitoring; and in cases of complications, it can have a significant impact on a patient's health and even diminish life expectancy (American Diabetes Association, 2014). As Gambo *et al.* (2021) observed, the control of diabetes mellitus is experienced by several means. Therefore, T1DM requires lifetime treatment with exogenous insulin, which exposes patients to many problems (Soylu *et al.*, 2013). Maintaining the BG level in the normal range has been the goal of treating T1DM. Also, the complexity and uncertain nature of the patient's physiology further aggravates the problem of T1DM to a nonlinear and unobservable one. The resultant effect of this problem is hypoglycemia and hyperglycemia, which may lead to coma and eventually cause untimely death.

In this paper, our objective is to improve the accuracy of control and prediction of BG levels in patients suffering from T1DM to avoid the occurrence of hypoglycemia and hyperglycemia. We have formulated a mathematical model using carbohydrate counting, insulin requirements, and the Harris-Benedict energy equations to establish the framework for predicting and controlling BG level regulation in T1DM. We focused on the data collected from patients using an insulin pump to formulate the predictive control algorithm and implemented a portable system that validates the model's accuracy and adequacy. Specifically, we used patients with T1DM at the Center National Hospitalier Universitaire Hubert Koutoukou Maga (CNHU-HKM) in the Republic of Benin for the study.

Structure

Section 2 reviewed related works and established grey areas that require improvement. In section 3, we discussed the research methodology explaining the approaches used. In particular, we discussed the mathematical model, the formulated algorithm for prediction, our analysis's requirements and design specifications, and how the model was validated. Section 4 contains the system implementation that validates the framework's accuracy. In section 5, we discussed the empirical analysis. The results and discussion are provided in section 6. Finally, we presented the concluding remarks from our work in section 7 and gave some ideas for future work.

RELATED WORK

According to the document produced by the International Medical Device Regulators Forum (IMDRF, 2014) and other related literature (e.g., McHugh *et al.*, 2012; Pashkov *et al.*, 2016), software systems has an essential role in therapeutic devices for providing safety in the advancement of healthcare delivery (Lee *et al.*, 2006). These devices' engineering process requires an appropriate RE approach to capture the device's real intentions based on users' expectations. A typical example of devices used for administering healthcare services includes: continuous glucose monitoring (CGM) system (Langendam *et al.*, 2012; Joubert and Reznik, 2012; Hirsch *et al.*, 2008; Rodbard, 2017), an insulin pump (Weissberg-Benchell *et al.*, 2003; Bergenstal *et al.*, 2010), wearable devices that can monitor, control multiple aspects of the patient's vital physiology (Mendelson *et al.*, 2006) such as heart rate, BG level and skin temperature (Halperin *et al.*, 2008).

Recent research in predictive modeling focused on understanding the patient's physiologic states (Cohen, 2012; Carson and Cobelli, 2013; Ghassemi *et al.*, 2014), and the development of adaptive control algorithms that can deliver personalized treatments for patients with diabetes (Lunze *et al.*, 2013; Gao *et al.*, 2017). Specifically, the investigation of the management of diabetes has accumulated significant consideration, particularly regarding the advancement of procedures and algorithms that rely on monitoring parameters by using sensing and actuating devices. To this end, many researchers have made efforts to produce control algorithms to boost the treatment of diabetic patients (for example, Albisser *et al.*, 1974; Parker *et al.*, 1999; Li *et al.*, 2016; Gao *et al.*, 2017).

Noticeably, additional models and approaches have been broadly considered in the past. Examples include: the proportion of integration differentiation (PID) (Watson *et al.*, 2011), model predictive control (MPC) (Lee *et al.*, 2009), fuzzy logic control (Grant *et al.*, 2007), neural network model (Tresp *et al.*, 1999; El-Jabali, 2005; Pappada *et al.*, 2011), grammatical evolution (Contreras *et al.*, 2017) and Random Forests (Georga *et al.*, 2012). These models mainly focused on predicting BG concentration, distributing insulin, and estimating the meal relevant to our study.

The traditional BG monitoring system still poses technological challenges to the automatic control of BG levels (Magni *et al.*, 2007; Villena Gonzales *et al.*, 2019). We have considered some differences and works that have been done in the models mentioned above (see Watson *et al.*, 2011; Lee *et al.*, 2009; Grant *et al.*, 2007; Tresp *et al.*, 1999; El-Jabali, 2005; Pappada *et al.*, 2011; Contreras *et al.*, 2017 and Georga *et al.*, 2012) to guide the analysis and design process of our approach. For example, we observed that the MPC system was compared with the standard PID controller by Magni *et al.*

(2007) in terms of its performance. Magni *et al.* (2007) used the low blood glucose index (LBGI) and high blood glucose index (HBGI) as performance indices. The result showed that MPC had better results amidst the uncertainty of meals with 40% in regulation than PID.

In the work of Ellingsen *et al.* (2009), MPC was seen to contain dynamic requirements and insulin on board (IOB). Ellingsen *et al.* (2009) used the IOB to structure a predictive model that controls glycemia through exogenous insulin. The results showed that half of the simulations led without IOB brought hypoglycemic, compared to 10% with IOB. In terms of achieving adequacy and safety in BG control, the IOB imperative can abrogate aggressive control moves (with a huge insulin dose), thereby limiting the danger of hypoglycemia.

In Pappada *et al.* (2011), a neural network model (NNM) was structured based on diabetic patients' expectations for glucose since they are on insulin. In this regard, the authors used the value from continuous glucose monitor (CGM), insulin, diet, and stress variable as datasets. The performance evaluation gave 43.9 mg/dl and 22.1 mg/dl as RMSE and MAE, respectively. Besides, the results showed that 88.6% of patients with diabetes are in the normal range, 72.6% are hyperglycemic, 2.1% are hypoglycemic, and 13.9% are norm glycemic. Pappada *et al.* (2011) provided the guideline and direction for detecting hypoglycemia and hyperglycemia episodes. Also, Georga *et al.* (2012) work on subcutaneous glucose concentration in patients with T1DM using Random Forests (RF) regression technique.

In another work by Georga *et al.* (2012), glucose, energy expenditure during physical activities, food intake, and insulin injections were used for the experiment. The authors used RMSE and the average correlation coefficient to prove their approach's adequacy. The RMSE, on average, gave 6.60, 8.15, 9.25, and 10.83 mg/dl within the time frame of 15, 30, 60, and 120 mins, respectively. However, Georga *et al.* (2012) did not consider the stress factor, which in most cases causes hyperglycemia. Also, Georga *et al.* (2013) used support vector regression (SVR) to predict the subcutaneous glucose concentration. The RMSE, on average, gave 5.21, 6.03, 7.14, and 7.62 mg/dl within the time frame of 15, 30, 60, and 120 mins, respectively. However, the time 120min is too short; in most cases, it can vary due to food and insulin absorption delays.

In the same vein, Balakrishnan *et al.* (2013) developed a personalized hybrid model to predict BG in children and adolescents with T1DM. BG values, carbohydrate count, perceived exercise rate (RPE), basal insulin, and bolus insulin doses were collected. The Hybridized model was formulated based on the dynamism in meal and insulin absorptions. The emphasis of Balakrishnan *et al.*'s (2013) work was tailored towards preventing adverse effects on patients with T1DM in terms of hypoglycemia and hyperglycemia occurrence. Li *et al.* (2016) based their BG prediction on pooled-panel-data (PPD) and a pre-clustered personalized regression technique. Compared with techniques such as support vector machine (SVM), decision tree (DT), and random forest (RF), the prediction by Li *et al.* (2016) gave better accuracy. It addressed the problem of the sparsity of data. Suffice it to say, Li *et al.* (2016) approach requires extensive historical data of patients with T1DM to engender good prediction with high precision. This requirement cannot be met (for example, in a new patient).

In Bazaev *et al.* (2017), a predictive algorithm was proposed to estimate and adjust the insulin dose. The focus was on the artificial pancreas based on the sigma model. Bazaev *et al.* (2017) approach enabled patients to avoid incorrect insulin doses and reduce potential dangers. Additionally, the system gives patients an alarm when their BG levels change unpredictably. Although this approach allows the patient to set information about the meal, it cannot handle the high rise in BG. The algorithm also considered technological factors, such as: noise, dysfunction of the insulin pump, and BG calibration. The evaluation showed that relative error is 15.7 mg /dl and rectified 97.5% of mistakes.

In another study by Gao *et al.* (2017), the LaGrange interpolation method was used to control close-loop glucose and insulin to solve data errors. However, even though the approach gave an excellent performance in the relationship between glucose and insulin values, it is deficient in making quick changes in insulin values when the patient's BG level increases or decreases rapidly. The closed-loop control system by Faiz *et al.* (2017) and Hassan and Riaz (2017) was designed to normalize high BG

levels. In this regard, the Bergman minimal mathematical model was used for feedback linearization. Despite the reduction in the total time of hyperglycemia by 88%, it is impossible to forestall extreme hyperglycemia because of the risk involved during meal intake and insulin type.

On the other hand, Contreras *et al.* (2017) used a hybridized approach to predict BG. In particular, they used grammatical evolution and physiological frameworks. After collecting and analyzing BG values, food, and insulin, the BG prediction outcome was promising, with an average of 98.31% prediction. Contreras *et al.*'s (2017) hybridized approach is suitable when there is a sensor failure. Apart from that, Contreras *et al.*'s (2017) approach is most appropriate when predicting short-term BG values and detecting sensor errors in the continuous glucose monitoring system.

In 2018, Pustozarov *et al.* (2018) developed and evaluated a mobile, personalized BG prediction system. Data were collected from patients with gestational diabetes mellitus using glucometers. The result after prediction gave 0.87mmol/L and 0.69mmol/L RMSE and MAE, respectively. However, the accuracy had shown an error mean absolute percentage error of 12.8%. The model is not suitable for predicting postprandial glucose response time when insulin injection is administered.

In summary, based on the literature works above, simple measurement of BG and the administration of immediate corrective insulin doses are not sufficient to control long-term BG in patients with T1DM. We strongly observed that administered insulin could not be expelled from the body once injected. Differently, in our research, we introduced the need for a RE approach to gain adequate insight into what is expected to give patients with T1DM better care with the use of programmable controllers. Consequently, controllers must consider insulin sensitivity, diet, and physical activity to oppose this variation.

METHODOLOGY

We followed qualitative and quantitative approaches in case study research (Yin, 2017; Runeson *et al.*, 2012) to achieve our study's objective. We used structured interviews, observation, and inspection of organizational documents to collect and analyze data for qualitative research. Patients with T1DM and medical doctors (experts) are the target audience for data. For the quantitative approach that supports measurement based on data, we formulated a mathematical model using carbohydrate counting, insulin requirements, and the Harris-Benedict energy Equations to establish the framework for predicting and controlling BG level regulation in T1DM.

Figure 1 provides a schematic view of our approach. More precisely, our approach considers the effect of diet, physical activity, and stress. The objective is to predict the BG level in patients with T1DM accurately. As Figure 1 reflects, carbohydrates from food intake, physical activity, and stress are computed in the controller to calculate the insulin dose's net amount administered to the patients via the insulin pump. Next, the controller computes the insulin dose's action time to provide information on the remaining dose left in action. The extra insulin dose from the previous insulin dose lowers the next insulin dose value and changes the next insulin dose. In this case, the system predicts the BG level and sends feedback to the physician. Patients with T1DM can view physicians' recommendations or instructions to avoid hypoglycemia, hyperglycemia, and even coma.

Mathematical Model for Predicting Blood Glucose

The mathematical model is aimed at managing the BG level and insulin dose. We considered external factors that affect the BG described by Gao *et al.* (2017). Examples of these external factors include the patient's diet and daily exercises that are part of the patient's routine and activities. We assumed that external factors are responsible for the delay in insulin absorption and BG variation. Our model formulation has used some essential terms to formulate the mathematical equations. These terms include: (i) the total daily insulin dose (TDD); (ii) the basal insulin and bolus insulin dose; (iii) the carbohydrate factor (CarbF); (iv) the insulin correction factor (CorrF); (vii) the bolus on board (BOB); and (viii) the basal metabolic rate (BMR).

Figure 1. A schematic view of our approach

We have captured the TDD in equations (1a) and (1b), respectively (Walsh *et al.*, 2013):

$$TDD(adults) = Weight(Kg) * 0.53 [IU / d] \quad (1a)$$

$$TDD(children) = Weight(Kg) * 0.44 [IU / d] \quad (1b)$$

The CorrF can be approximated in mg/dl, as shown in equations (2a) and (2b), respectively:

$$CorrF(Regular\ insulin) = \frac{1500}{TDD} [mg / dl] \quad (2a)$$

$$CorrF(Rapid\ acting\ insulin) = \frac{1800}{TDD} [mg / dl] \quad (2b)$$

The CarbF formula can be represented in mg/dl, as shown in equations (3a) and (3b), respectively:

$$CarbF(Regular\ insulin) = \frac{450}{TDD} [mg / dl] \quad (3a)$$

$$CarbF(Rapid\ acting\ insulin) = \frac{500}{TDD} [mg / dl] \quad (3b)$$

BMR Formulas are represented in equations (4a) and (4b), respectively (Bardutzky *et al.*, 2004):

$$\text{Men: BMR (kcal)} = 665 + 13.75 \times W + 5.0 \times H - 6.78 \times A \quad (4a)$$

$$\text{Women: BMR (kcal)} = 655 + 9.56 \times W + 1.85 \times H - 4.68 \times A \quad (4b)$$

where:

W = weight in kilograms

H = height in centimeters

and:

A = age in years

Thus, our mathematical formulation for predicting and controlling BG is based on the equations described in (5) to (15) below. Hence, the predicted BG value is formulated as follows:

$$G(t+1) = G(t) + \text{CorrF} [C(t) - I(t) - E(t)] \quad (5)$$

where $G(t)$ is the current BG value, $I(t)$ is the level of BG, by which the initial BG is decreased due to insulin action (Daskalaki *et al.*, 2012), $C(t)$ is the level of BG by which the initial BG is increased due to the carbs action, $E(t)$ is the level of BG by which the initial BG is decreased due to physical activity, and CorrF .

Therefore, we represent the total insulin absorption, as indicated in Equation (6):

$$I(t) = I_{\text{basal}}(t) + I_{\text{actualbolus}}(t) - I_{\text{actualBOB}}(t) + \sum I_{\text{prevBOB}}(t-1) \quad (6)$$

$$I_{\text{actualBOB}} = (I_{\text{bolus}}) * \left(1 - \frac{t_1}{5}\right) \quad (7)$$

$$I_{\text{prevBOB}} = I_{\text{prevbolus}} * \left(1 - \frac{t_2}{5}\right) \quad (8)$$

The amount of basal insulin dose is represented every hour, as shown in Equation (9):

$$I_{\text{basal}}(t) = \frac{I_{\text{basal}}}{24} \quad (9)$$

Combining equations (7), (8), and (9) replaced in (6), the equation of insulin in predictive action $I(t)$ can lead to the changes in BG, as shown in Equation (10):

$$I(t) = I_{\text{basal}} + \frac{t_1}{5} * I_{\text{actualbolus}} + \sum_{t=1}^n I_{\text{prevbolus}} * \left(1 - \frac{t_2}{5}\right) \quad (10)$$

where t_1 means the time between the insulin dose injected and the prediction time, t_2 is the time between previous insulin dose and prediction time, $I_{correctionBolus}$ refers to insulin given to correct a BG level that is out of target range, I_{basal} is basal insulin dose planned to be taken, $I_{actualbolus}$ is the current bolus insulin dose, $I_{prevbolus}$ is the previous bolus insulin dose, $I_{prevBOB}$ is insulin that is still in action from last insulin dose, and $I_{actualBOB}$ is the remaining current insulin dose.

The carbohydrate action is defined in Equation (11):

$$C(t) = \frac{R_a(t)}{CarbF} \quad (11)$$

with:

$$R_a(t) = \frac{Carb * Carb_{BIO} * t * e^{(-t \setminus t_{max,G})}}{t_{max,G}^2} \quad (12)$$

By replacing equation (12) in (11), the final equation of carbs can be represented as Equation (13):

$$C(t) = \frac{Carb * Carb_{BIO} * t * e^{(-t \setminus t_{max,G})}}{CarbF * t_{max,G}^2} \quad (13)$$

where $t_{max,G}$ (min) is the maximum time of BG appearance rate, Carb is the amount of carbohydrates ingested during a meal, CarbF is Carbohydrate Factor, and Carb_{BIO} is carbohydrate bioavailability. $Ra(t)$ is the BG absorption rate. As observed in Hovorka *et al.* (2004), $t_{max,G} = 40$ min and $Carb_{BIO} = 0.8$.

Physical activity and stress action are represented as shown in equation (14):

$$E(t) = \frac{BMR * Activity \ level * Stress \ factors * d}{1440 * 4 * CarbF} \quad (14)$$

with d, duration of physical activity, BMR, Body Mass Index.

Thus, considering Equations (10), (13), and (14), replaced in Equation (5), predicted BG at time t could be represented, as shown in Equation (15):

$$G(t+1) = G_o + CorrF \left[\frac{Carb * Carb_{BIO} * t * e^{(-t \setminus t_{max,G})}}{CarbF * t_{max,G}^2} - t_1 * I_{basal} - \frac{t_1}{5} \left(I_{actualbolus} \right) - \sum_{i=1}^n \left(I_{prevbolus} \right) * \left(1 - \frac{t_2}{5} \right) - \frac{BMR * Activity \ level * Stress \ factors * d}{1440 * 4 * CarbF} \right] \quad (15)$$

The algorithm in Figure 2 describes the step-by-step process for predicting BG. The algorithm is structured into three (3) parts, consisting of: (i) the collection process of insulin dose to determine

Figure 2. Algorithm: Framework of blood glucose prediction

Constant:

Post meal BG target $G_1 = 80\text{mg/dL}$; Pre meal BG target $G_2 = 180\text{mg/dL}$; $t_{\max, G} = 50 \text{ min}$; $\text{Carb}_{BIO} = 0,8$

Input:

BG for current date and actual moment, $G(d, t)$; last date and last moment $G(d-1, t)$, current and last moment $G(d, t-1)$, Insulin for current date and moment $I_{\text{basal}}(d, t)$;
Basal insulin for current date and last moment $I_{\text{basal}}(d, t-1)$;
Bolus insulin for current date and moment $I_{\text{basal}}(d, t)$; current date and last moment $I_{\text{basal}}(d, t-1)$; Insulin dose in action $I(d, t)$; CorrF , CarbF ; Carb ; IS ; Food Portions serving size s , Amount of carbohydrates Q_{carb} ; Amount of Dietary Fiber Q_{fiber} , Amount of sugar alcohol $Q_{\text{sugar-alcohol}}$; Amount of Polydextrose $Q_{\text{Polydextrose}}$, $t_{\text{prevbasal}}$, $t_{\text{prevbolus}}$

Output:

$G(d, t+1)$, event

Begin

Calculate the remaining insulin dose from the previous insulin dose

1: **for** each $t \in [0, n]$ **do**

2: **if** $(t+1 - t_{\text{prevbolus}}) \leq 5$ **then**

3: $I_{\text{prevBOB}} = I_{\text{bolus}}(d, t-1) * (1 - (t+1 - t_2) / 5)$

4: **else**

5: $I_{\text{prevBOB}} = 0 \text{ IU}$

6: **end if**

Calculate the bolus insulin dose

7: **if** $(t = \text{fasting time})$ **then**

8: **if** $(G(d, t) > G_1)$ **then**

9: $I_{\text{actualbolus}} = (G(d, t) - G_1) / \text{CorrF}$

10: **else**

11: $I_{\text{actualbolus}} = 0 \text{ IU}$

12: **end if**

13: **else if** $(t = \text{pre-meal time or } t = \text{bedtime})$ **then**

14: **if** $(G(d, t) > G_2)$ **then**

15: $I_{\text{actualbolus}} = (G(d, t) - G_2) / \text{CorrF}$

16: **else**

17: $I_{\text{actualbolus}} = 0 \text{ IU}$

18: **end if**

19: **else**

20: $I_{\text{actualbolus}} = 0 \text{ IU}$

21: **end if**

22: **end if**

23: $I(d, t) = t_1 * I_{\text{basal}} + (t_1) * (I_{\text{actualbolus}}(d, t) / 5 + I_{\text{prevBOB}}$

24: $\text{Carb} = s * (Q_{\text{carb}} - Q_{\text{fiber}} - \frac{1}{2} * Q_{\text{sugar-alcohol}} - Q_{\text{Polydextrose}})$

25: $C(d, t) = \frac{\text{Carb} + \text{Carb}_{BIO} * t * e^{(-t/t_{\max, G})}}{\text{CarbF} * t_{\max, G}^2}$

26: Compute $E(t)$

27: Compute $G(d, t+1) = G(d, t) + \text{CorrF} * (\text{Carb} - I(d, t) - E(t))$

28: **return** $G(d, t+1)$

29: **if** $(G(d, t+1) < G_1)$ **then**

30: event = "Hypoglycaemia"

31: **else if** $(G(d, t+1) > G_2)$ **the**

32: event = "Hyperglycaemia"

33: **else**

34: event = "Normal"

35: **end if**

36: **end if**

37: **end for**

End

the I_{basal} , I_{bolus} , $I(t)$ and the previous values; (ii) the calculation of the carbohydrates that are absorbed $C(t)$; and (iii) the determination of the next BG values given as $G(t+1)$. The parameters used for the BG prediction are described in Table 1.

We evaluated our model's performance using two different evaluation metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The calculations of these metrics are given in Equations 16 (Chai *et al.*, 2014; Li and Fernando, 2016) and 17:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (p_i - y_i)^2}{n}} \quad (16)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |p_i - y_i| \quad (17)$$

From equations (16) and (17), the variable p stands for the predicted BG level, y stands for the actual BG level, and n is the number of BG measurements taken.

Analysis and Design Specification

In Tables 2, 3, and 4, we showed the requirement specifications of the BG prediction system, which includes: user requirements, functional requirements, and non-functional requirements, respectively.

Table 1. Parameters used for the model

S/N	Parameters	Description	Units
1	G_o	current BG	mmol/l
2	$CorrF$	indicates how much a patient's BG drops with each unit of insulin	mmol//IU
3	I_{basal}	basal insulin dose planned to take	IU
4	I_{bolus}	bolus insulin dose (refers to the insulin given to correct a BG level that is out of target range)	IU
5	TDD	total Daily Insulin Dose	IU
6	I_{prevBOB}	insulin, which is still in action from the previous insulin dose	IU
7	IS	insulin sensitivity (how much insulin a patient needs to move a certain amount of glucose into cells)	mmol//IU
8	$Carb$	amount of carbohydrates ingested during a meal	g
9	$CarbBIO$	the fraction of Carb absorbed	constant
10	t_{max}, G	the maximum time appearance rate of glucose	min
11	BMR	basal Metabolic Rate	Kcal
12	$CarbF$	carbohydrate-to-insulin ratio (estimate the grams of carbohydrate that are covered by 1 unit of insulin)	mmol//IU
13	$E(t)$	energy expenditure refers to how many calories per time a patient will burn during the activity.	Kcal
14	t_i	the time between the insulin dose injected and the prediction time	Hour
15	d	duration of physical activity	Hour
16	t_2	the time between the previous insulin dose and the prediction time	hour

As mentioned earlier, the system users comprise the patients, diabetes specialists, and nutritionists/dietitians. Each type of user has a range of varying accessibilities to the system. While the user requirements in Table 2 describe what the user wants to do with the system, the functional requirements in Table 3 describe what the system will do and how to react to particular inputs (Pohl, 2010). On the other hand, the non-functional requirements in Table 4 describe the desired characteristics when using the system by the user.

Furthermore, the BG level prediction design process followed the RE process's initial phases from a software engineering perspective (Pohl, 2010; Classen et al., 2008). More precisely, we represented the patients with T1DM, diabetes specialists, and nutritionist/dietician as the primary actors in a use case diagram shown in Figure 3. The use case diagram describes how the system was broken down into structural parts regarding the behavior and functionality. Also, it provides the working blueprint upon which a functional system was implemented and assignments of rights and privileges on the system. As Figure 3 reflects, patients with T1DM, Diabetics Specialist, and Nutritionists or Dietitians are the primary actors. Their corresponding functions in the BG prediction are also shown. For example, patients with T1DM login into the system and connect to the BG measurement devices (CGMS) and the insulin pump. The system collects the current BG levels at each step (fasting BG, post-meal BG, pre-meal BG, and before bedtime). It saves them into the database for further investigations. The nutritionist views the patient's food entries and provides the next food plan based on hypoglycemic and hyperglycemic events. The diabetes specialist can view periodic BG level values reported and recommend the patient's appropriate insulin dose. After that, the patient checks the BG level predicted and follows the instructions given by the diabetes specialist to avoid hypoglycemia and hyperglycemic events.

Table 2. User Requirements

URiD	Requirement Description
UR1	Patients with T1DM will be able to input their login credentials into the system.
UR2	Patients with T1DM will be able to input their profile information on the user interface.
UR3	Patients with T1DM must be able to view BG's measurement values periodically recorded by the system.
UR4	Patients with T1DM should input their eating time, size, and food through the system.
UR5	Patients with T1DM will be able to input the amount of each nutrient from food intake such as (carbohydrate, dietary fiber, sugar, alcohol, polydextrose) from the Food Nutrition Facts Panel on the user interface.
UR6	Patients with T1DM will be able to view the number of Carbs from food intake.
UR7	Patients with T1DM will be able to input basal insulin, correction insulin, bolus insulin, and mealtime insulin doses.
UR8	Patients with T1DM will be able to input physical activities, frequency, stress factors, and goal weight.
UR9	Patients with T1DM shall be able to view the predicted BG.
UR10	Patients with T1DM will be alerted by the system for possible cases of hypoglycemia and hyperglycemia events.
UR11	Patients with T1DM shall view instructions records and the food and weight management plans.
UR12	Patients with T1DM and Physicians can view the past input values such as the BG history levels and how they varied over time.
UR13	Physicians shall have access to the reports of the patient's progress.
UR14	The nutritionist/dietician is responsible for creating a food plan for patients with T1DM and provides a list of prohibited foods.
UR15	The diabetes specialist can view and analyze the predicted BG level.

Table 3. Functional Requirements

FRiD	Requirement Description
FR1	The system shall monitor the predicted BG levels and insulin dose continuously.
FR2	The system must accept valid input of registered patients of T1DM information details.
FR3	The system should notify patients that the next BG prediction will be low or high.
FR4	The system shall compute the right insulin dose, covering the carbohydrate from food intake and the basal insulin to avoid hyperglycemia events.
FR5	The system shall remind the patient to eat carbohydrate food based on a food plan or hypoglycemia correction.
FR6	The system will send a notification message to the patient to remind future food estimation.
FR7	The system should generate feedback to use the system by the user.
FR8	The system generates feedback notifications in helping the patient control their daily calories based on their body mass index.
FR9	The mobile app will communicate with wearable sensors (insulin pump and glucose monitor) through Bluetooth.
FR10	The system shall manage hypoglycemia and hyperglycemia events alerts.
FR11	The system shall secure the patient's data during the encryption and decryption process.
FR12	The system will be user-interactive to allow easy procedure of predicting BG using the app.
FR13	The system shall notify the patient by message or voice.
FR14	The system will provide an exportable spreadsheet of all patient information to the physician.
FR15	The system shall generate graphical reports to the physician in chart types: line chart, area chart, time chart, bar chart, and pie chart.

Table 4. Non-functional Requirements

NFRiD	Requirement Description
NFR1	The system should be extensible; that is, there may be a possibility of adding or modifying features.
NFR2	The system should be compatible with all android platforms from version 4.2 and above.
NFR3	The system should be easy to learn and useable by sophisticated and novice users.
NFR4	The system should be maintainable and upgradable.
NFR5	The system must act within a specific time, regardless of the user's action.
NFR6	The system should be highly secured.

Moreover, we graphically represented the BG prediction system's process behavior in an activity diagram shown in Figure 4. The goal is to show how data are controlled and flowed in the prediction process. In particular, the system will frequently check the remaining insulin dose from the previous insulin dose. If it remains in some quantities, the next insulin dose will be reduced from the actual remaining insulin to prevent the BG from going down and causing hypoglycemia. If not, it checks the patient's registered food intake. The other side of the coin shows that it computes the insulin-to-carbohydrate action to cover the food intake by which the initial BG is increased. In the case of programmed physical activity, the system calculates the energy expenditure by which the initial BG is decreased. All of this information is required to use the formulated mathematical model.

Figure 3. Use case diagram featuring patients with T1DM, diabetes specialists, and nutritionist/dietician as the primary actors

Figure 4. BG prediction system's process behavior

SYSTEM IMPLEMENTATION

We put into use an interactive system to empirically demonstrate our mathematical model's capability and design specifications in sections 3.1 and 3.2, respectively. The Mobile-Based Blood Glucose Prediction System (MbBGPS) was implemented on a 64-bit Windows 10 Pro Operating System (OS) with an Intel(R) Core™ i7-2670QM CPU @ 2.20 GHz processor and 12GB RAM. We used Java programming language in the Integration Development Environment (IDE) IntelliJ to develop the MbBGPS, which we built into a mobile application. We deployed the mobile application on the Android platform to allow ease of use. However, we have estimated the total cost for implementing MbBGPS to be about six thousand five hundred dollars (\$6,500.00) only. Figure 5 describes the main menu page of the MbBGPS.

The main menu page in Figure 5 contains the various lists of activities of the MbBGPS. Similarly, the BG prediction button enables patients to view BG's next value, insulin dose, carbohydrate, and

Figure 5. Main menu page of the MbBGPS

physical activity report. The BG measurement button allows the patient to sense the BG readings with CGMS via Bluetooth, or record the measurement time and type, periodically. The meal intake button enables patients to record all information (food serving size, food name, amount of sugar-alcohol, amount of fibers, amount of Polydextrose, and food intake time) about the meal intake.

The insulin dose button allows patients to input information about insulin, such as insulin and insulin doses (basal insulin, bolus insulin dose, and correction bolus). The physical activity button allows patients to compute each physical activity's exercise time and level. It is used to estimate the energy expended during an exercise practice in terms of calories. The stress button enables the patient to enter the stress/injury-level information. The monitoring button generates graphical reports or charts. It allows patients to view and visualize the predicted BG values in real-time. After that, the report is sent remotely to the diabetes specialist and nutritionist to follow up on the patient. The button "Ask Doctor" establishes a chat communication platform between the patients and the doctor. Patients can also see diabetes specialists and nutritionists' recommendations and instructions for guidance to avoid hypoglycemic or hyperglycemic events. All information is based on prohibited food, the future food plan, or bolus insulin dose to counteract hypoglycemia and hyperglycemia, respectively. Finally, the patient uses the reminder button to set up alerts for the eating time and take correction insulin dose.

EMPIRICAL ANALYSIS

We conducted interviews that address the following: (i) current care guidelines and treatment methods; (ii) therapy for patients with T1DM; (iii) CGM, insulin injection devices, and other related accessories; (iv) weight management practices; and (v) food planning. We had access to study twelve thousand (12,000) case files of patients with diabetes; out of which we got one hundred and three (103) cases of patients with T1DM, and eleven thousand, eight hundred and ninety-seven (11,897) cases of patients with type 2 and gestational diabetes. Among the 103 cases of patients with T1DM, only fifty-two (52) patients were treated with insulin injections. They were eventually used for the study.

Thus, we administered the interview guide and questionnaire (IGQ) to both patients and doctors. For the patients, the IGQ provided a record of information on: (i) food intake (the type of food, serving size, and time (breakfast, lunch, and dinner)); (ii) insulin injections (type, dose, and time); and (iii) physical activity (type, intensity, and duration). The doctor's IGQ provided past BG levels and past insulin doses values in contrast. The food composition (calories, kind of food, portion size, and time) were post analyzed by a dietician. We pre-treated patients' data and converted it into time-series data before using it as inputs in our model formulation. BG levels and insulin dose values are given precisely, but the amount of food and physical activity were estimated. Relevant data such as insulin, bolus insulin, age, weight, and carbohydrate intake were extracted from the overall data collected. Table 5 contains the information obtained in connection with an explanation of the importance of each of them.

We expressed the data collected and analyzed as mean $\pm$ Standard Derivation (SD), as shown in Table 6. As shown in Table 6, the patients' age range is between 8 - 21 years, the body mass index (BMI) is 21.18 ± 2.64 kg/m², and the duration of diabetes is 5.65 ± 2.13 years. Noticeably, 58% of the patients are male (30 in number), while 42% are female (22 in number). We also discovered that all patients with T1DM have different insulin dose requirements, such as basal insulin and bolus insulin during the day, as shown in Figure 6. For example, patient N°24 had the highest insulin dose (80 IU), while patient N°17 had the lowest daily insulin dose (9IU). Thus, the patient with the highest amount of insulin dose has correction insulin in addition to basal insulin. The data relating to meal intake is shown in Figure 7, which indicates that all patients have a different amount of carbohydrates at each time (breakfast, lunch, and dinner).

As Figure 7 indicates, patients N°23 and N°2 have the same amount of carbohydrate (360grams), while patients N°48 and N°49 carbohydrates are under 100grams. This means that some patients did not eat at some times on the same day. A better illustration is shown in Figure 8

Table 5. List of Information Extracted from Data Collection and the Reasons for Extraction of Given Information

S/N	Information Extracted from the Patient's Data	Reason for its Extraction
1	Age, weight, height	To evaluate the basal metabolic rate (BMR) to determine the calorie need.
2	Time and value of pre-meal BG	To identify the daily period and pre-meal insulin dose.
3	Time and value of post-meal BG	To identify the daily period and post-meal insulin
4	Insulin doses and action time	To identify the amount of insulin dose, bolus insulin, basal insulin, and the total of the daily insulin dose.
5	Type of food, portion, eating time	To identify the net amount of carbs from food intake.
6	The time between the insulin dose and the food intake	To define how long a patient waits for an insulin action before they start to eat.
7	Addition of previous insulin dose registrations	To identify the remaining insulin dose in action and detect the occurrence of hypoglycemia events.
8	Addition of carbohydrate registrations	To identify the bolus insulin dose and detect the occurrence of hyperglycemia events.
9	Insulin ratio calculated from the carbs and insulin dose	To identify the insulin dose that can cover the carbs action.
10	Physical activity level and stress factor	To evaluate the BG fluctuations.

Table 6. Profile Characteristics of Fifty-Two (52) Patients with T1DM (Gambo et al., 2021)

S/N	Characteristics of Fifty-two (52) Patients with T1DM	
1	Age (years) Range	(8 – 21)
2	Sex Male Female	30 (58%) 22 (42%)
3	Weight (kg) Range Mean $\pm$ SD	23.9 – 53.5 39.60 $\pm$ 12.97
4	Duration of T1DM (years)	5.65 $\pm$ 2.13
5	HbA1c (NGSP; %)	7.5 $\pm$ 1.01
6	Body Mass Index (kg/m ²) Range Mean $\pm$ SD	15.72 – 27.98 21.18 $\pm$ 2.64
7	Insulin dose (IU) Mean Total Daily Insulin (IU/day) Insulin Bolus Insulin Basal	38.33 25.27 $\pm$ 11.64 16.75 $\pm$ 10.91

Legend: SD = Standard Derivation

between patient N°2 and N°23. They both have the same amount of daily carbohydrates. However, they have a different amount of carbohydrate at breakfast– 90 grams for patient N°2 and 84 grams for patient N°23. On some days, the BG level predicted is very similar to the measured one; for instance, patients N°24 and N°48, as shown in Figure 9 and Figure 10, respectively. This shows that predicting future values is possible with a long prediction horizon during the day. However,

Figure 6. Total daily insulin dose

Figure 7. Food intake

there are often full days or only particular cases within one day that is significantly different. As an example, looking at the day of patients N°3 and N°50, as shown in Figure 11 and Figure 12, respectively, where the predicted values are all similar but in some times are profoundly different, particularly at 12:00 PM, 5:00 PM, and 6:00 PM. This is a typical example of an unexpected factor that might appear around the eating time that the BG was measured. The same can be with an insulin dose to substitute the food or carbohydrate intake that was not registered but makes the predicted BG higher than it was.

Figure 8. Food daily intake between patient 2 and patient 23

Figure 9. Variation of current BG and predicted BG for Patient 24

RESULTS AND DISCUSSION

For the fifty-two (52) patients with T1DM, the average RMSE and MAE are 0.3856 and 0.4483 mmol/l, respectively, with a good prediction of 96%. Table 7 showed the model's quantitative measures for fifty-two (52) patients with RMSE and MAE. As reflected in Table 7, the BG changes trend is maintained in all cases. Also, Table 7 revealed that two (2) patients (that is, Patients N°21 and N°50) exceeded the recommended value of 1.0 mmol/l of absolute error (American Diabetes Association, 2014), while fifty (50) patients kept the value within the range of less than 1 mmol/l. Consequently,

Figure 10. Variation of current BG and predicted BG for Patient 48

Figure 11. Variation of current BG and predicted BG for Patient 3

the prediction for two (2) patients with T1DM (that is, Patients N°21 and N°50) was not good enough with 1.7151 and 1.078 mmol/l of RMSE, 1.0560 and 0.6999 mmol/l of MAE, respectively, while the remaining fifty (50) patients had good predictions between 0.1008 mmol/l and 0.9185 mmol/l.

Figures 9 to 12 showed the BG levels curve for four (4) patients. Each of these figures indicates the current and expected BG levels with different colorations and shapes for a different time. In these figures (Figure 9 to 12), we showed peaks that suggest the mealtime for the entire day. Some anticipated

Figure 12. Variation of current BG and predicted BG for Patient 50

curves preserve the pace and are approximately comparable to the measured curve for patients N°24 and N°48. In contrast, others have a different speed at regular intervals for patients N°3 and N°50.

Furthermore, we compared our RMSE and MAE model evaluation results with the following models: (i) Support Vector Regression (SVR) (Georga *et al.*, 2013); (ii) Random Forest (RF) (Georga *et al.*, 2012); (iii) Grammatical evolution (GE) (Contreras *et al.*, 2017); (iv) Pooled Panel Data (PPD) (Li *et al.*, 2016); and (v) Artificial Neural Network (ANN) (Pappada *et al.*, 2011). Table 8 showed the comparison results, which reveal that our model's RMSE and MAE had a smaller value of 6.95 mmol/l and 8.06 mmol/l, respectively. Remarkably, our model had less error rate in terms of RMSE and MAE, which indicates a better fit with reasonable accuracy. As observed in Willmott *et al.* (2005), lower estimations of RMSE shows a better fit. This means the model can be adopted to build an artificial pancreas system to control and monitor the BG levels of patients with T1DM.

Worthy of mention is that we are aware that class imbalance in the dataset is a common problem that directly affects the accuracy of the predictive model. As a future research plan, this problem will be resolved by re-sampling the original dataset either by oversampling the minority class or under-sampling the majority class. The synthetic minority over-sampling technique (SMOTE) (Chawla *et al.*, 2002) will be our choice approach to use. The goal will be to identify each attack essential to reduced features separately.

CONCLUSION AND FUTURE WORK

This paper formulated a mathematical model using carbohydrate counting, insulin requirements, and the Harris-Benedict energy Equations to establish the framework for predicting and controlling BG levels in patients with T1DM. Also, we implemented the framework as a portable system to allow ease of use. We evaluated RMSE and MAE's performance to prove the adequacy of our model in a case study. We noted that the system's goal is to support self-assessment and management of diabetes mellitus and facilitate reports of patients' daily situations.

To a considerable extent, the research opined that better carbohydrate counting, a better estimation of insulin in action from the previous insulin doses, and better BG monitoring could rapidly change the

Table 7. Results of fifty-two (52) patients, including the number of BG, MAE, and RMSE measurements

Patient No.	No. of BG Measurements	MAE [mmol/l]	RMSE [mmol/l]
1	8	0.2619	0.1008
2	7	0.3795	0.2106
3	9	0.4817	0.3202
4	10	0.2939	0.1580
5	7	0.6688	0.8671
6	13	0.7342	0.8276
7	7	0.3393	0.2001
8	8	0.3644	0.2239
9	8	0.4932	0.3855
10	8	0.4073	0.2557
11	8	0.3249	0.1795
12	10	0.7796	0.8681
13	8	0.7905	0.9185
14	8	0.3346	0.1890
15	7	0.2969	0.1330
16	9	0.4801	0.3448
17	7	0.2739	0.1343
18	8	0.6580	0.7079
19	8	0.7378	0.7952
20	13	0.3829	0.3056
21	13	1.0560	1.7151
22	12	0.3319	0.1802
23	8	0.4615	0.2977
24	8	0.1284	0.0260
25	14	0.5617	0.9542
26	8	0.3634	0.2187
27	8	0.5567	0.5169
28	12	0.4850	0.4223
29	7	0.4101	0.2502
30	15	0.3229	0.1596
31	8	0.3945	0.2383
32	8	0.2676	0.1180
33	12	0.3453	0.1905
34	9	0.3450	0.1688
35	8	0.2734	0.1077

continued on following page

Table 7. Continued

Patient No.	No. of BG Measurements	MAE [mmol/l]	RMSE [mmol/l]
36	11	0.3268	0.1544
37	6	0.6555	0.6555
38	8	0.4220	0.2860
39	8	0.3689	0.2101
40	8	0.4805	0.3374
41	7	0.6713	0.8882
42	8	0.4102	0.2772
43	7	0.3079	0.1620
44	13	0.2875	0.1258
45	12	0.4589	0.3813
46	8	0.4656	0.3586
47	8	0.3003	0.1537
48	8	0.2865	0.1141
49	7	0.3658	0.1969
50	8	0.6999	1.0788
51	18	0.3483	0.260
52	13	0.6700	0.7240
Total		0.4483	0.3856

Table 8. Comparative Analysis of Different Models

S/N	Metric	SVR	RF	PPD	GE	ANN	Our Model
1	RMSE (mmol/L)	7.62	10.83	39.43	26.62	43.9	6.95
2	MAE (mmol/L)	12.42	14.80	10.13	20.85	11.92	8.06

next BG trend without missing food and taking insulin at a defined time. It is pertinent to anticipate that our approach will provide immediate prediction and feedback to medical experts on how glucose affects patients' lifestyles with T1DM and how to prevent hypoglycemia and hyperglycemia. That is to say, our approach provides a way to make real-time adjustments about insulin changes, diet and activity patterns, and other factors. Besides, our research investigates the possibility of modeling glucose metabolism using a set of parametric data recorded from patients with T1DM.

In the future, we know it is essential to extend this research by taking note of the patient's school, study or work schedules, social situation, personality, cultural factors, or other medical conditions. As for the dataset, we hope that symptoms such as irritability, inability to concentrate, extreme thirst, dry mouth, weakness, headache, frequent urination, and sweating can be included. Although we know that some of these symptoms can be attributed to some underlying medical condition(s) the patient may be having. However, it is crucial to have a comprehensive look into all these with other specialists to improve the quality of care for patients with T1DM. We envision that this future task will require precise quantitative and qualitative recording.

Additionally, it will require estimating these symptoms and factors to achieve near normal glycemia, which might eventually delay the onset and the progression of many complications in T1DM. Momentarily, additional research can develop a model and system that integrates other medical embedded devices (for example, ACTi graph and ACTi heart), coupled with a photographic food recognition system that would minimize the patient's action from typing the food information in the system. This means that patients will no longer need to inform the system of their actions; instead, the system should recognize patients' activities and alert them.

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APPENDIX: LIST OF ACRONYMS

ANN: Artificial Neural Network
BG: Blood Glucose
BMI: Body Mass Index
BMR: Basal Metabolic Rate
BOB: Bolus On Board
CarbF: Carb Factor
CGM: Continuous Glucose Monitor
CNHU-HKM: Centre National Hospitalier Universitaire-Hubert Koutoukou Maga
CorrF: Correction Factor
DT: Decision Tree
FRiD: Functional Requirements iDentification
GE: Grammatical Evolution
HBGI: High Blood Glucose Index
IDE: Integration Development Environment
IGQ: Interview Guide and Questionnaire
IMDRF: International Medical Device Regulators Forum
IMDs: Implantable Medical Devices
IOB: Insulin On Board
LBGI: Low blood Glucose Index
MAE: Mean Absolute Error
MbBGPS: Mobile-Based Blood Glucose Prediction System
MPC: Model Predictive Control
NNM: Neural Network Model
NFRiD: Non-functional Requirements iDentification
OP: Operating System
PID: Proportion of Integration Differentiation
PPD: Pooled Panel Data
RE: Requirements Engineering
RF: Random Forest
RMSE: Root Mean Square Error
RPE: Perceived Exercise Rate
SD: Standard Deviation
SVM: Support Vector Machine
SVR: Support Vector Regression
T1DM: Type 1 Diabetes Mellitus
TDD: Total Daily Dose of Insulin
URiD: User Requirement iDentification

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