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# Noninvasive Blood Glucose Level Monitoring for Predicting Insulin Infusion Rate Using Multivariate Data

G. GEETHA*, J. Godwin PONSAM, K. NIMALA

*Department of Networking and Communications, School of Computing, SRM Institute of Science and Technology, Kattankulathur, India*

* *Corresponding Author e-mail: geethag@srmist.edu.in*

Diabetes stands as the most widely recognized acute disease globally, resulting in death when it is not treated in an appropriate manner and time. We have developed a closed-loop control system that uses continuous glucose, carbohydrate, and physiological variable data to regulate glucose levels and treat hyperglycemia and hypoglycemia, as well as a hypoglycemia early warning module. Overall, the proposed models are effective at predicting a normal glycemic range from >70 to 180 mg/dl, hypoglycemic values of <70 mg/dl, and hyperglycemic value of 180 mg/dl blood sugar levels. We undertook a seven-day, day-and-night home study with 15 adults. Initially, we started with checking insulin levels after meal consumption, and later, we concentrated on how our system reacted to the physical activity of the patients. Evaluation was conducted based on performance parameters such as precision (0.87), recall (0.87), $F$-score (0.82), delay ($26.5 \pm 3$), and error size ($1.14 \pm 2$).

**Keywords:** CGM, fog computing hypoglycemia, hyperglycemia, Apriori algorithm.



## 1. Introduction

Diabetes is one of the most dangerous and swiftly growing diseases in India. In the year 2015, there were 69.2 million people who lived with a diabetic condition in India, as reported by the World Health Organization (WHO). By 2030, there will be a drastic increase in this number in India, as stated by the International Diabetes Association [1].

In the healthcare sector, IoT devices generate massive and heterogeneous data, hence leading to storage issues. So, the reliance is placed on cloud computing techniques [2]. This hindrance can be eradicated by fog computing techniques. Fog computing is the technology that sits in the middle of the IoT and cloud computing, bringing computing power closer to IoT devices [3]. This is particularly relevant with the continuous improvement in the latest technologies such as body area network (BAN) and wireless sensor network (WSN) [4].

Blood glucose levels are constantly checked every day to assist patients in managing their well-being appropriately [5]. The input data concerning sugar levels is useful for the patients to manage their health on a daily basis. We designed a framework intended to screen the glucose level of individuals [6]. It is a self-administration device to provide treatment, shifting the focus from a traditional clinic-centered approach to a patient-focused view [7].

Connected healthcare allows many advanced digital healthcare solutions to work remotely, with extra components for continuous health monitoring and emergency detection, which could also alert people [8]. Individuals use a portable blood glucose measuring device called glucometer to check their glucose levels [9].

On the other hand, there are extremely noninvasive monitoring devices that quickly assess and show a person's blood glucose level in about a second without the patient's finger being pricked or causing any discomfort [10]. The glucose results are dealt with in the device and used to assess the HbA1c level utilizing a restrictive estimation. In these circumstances, blood glucose levels are tested every 1–2 hours [11].

Patients are advised on the appropriate amount of insulin to take and when to take it based on their food consumption, physical activity, and blood glucose level. To avoid frequent finger pricks, a continuous glucose monitoring (CGM) sensor to measure the diabetic patient's blood glucose level from the interstitial fluid is used [12]. Aside from CGM sensors, three other sensors have been used to measure blood pressure, BMI, and heart rate because they have very close relationships. 6LowPAN was used to collect data such as blood glucose, blood pressure, heart rate, and BMI from sensor nodes and send them to a smartphone [13]. Finally, if the blood glucose level becomes too low or too high, a push notification using MQTT will be broadcasted to physicians and patients to alert them of an emergency. Because sensor nodes generate data on a continuous and large scale, cloud computing techniques are used to analyze the critical data [14].

Our proposed system eliminates the redundant data in the fog node and sends only the long-time data into the cloud for storage, reducing bandwidth, latency, and storage space. Time-critical decisions are taken in the fog node and sent immediately to the patients; this will reduce response time and, in turn, increase the performance of the system. Before sending data to the cloud, all information is encrypted using the AES-256 algorithm, which gives more security for data transmission. Additionally, we devised a closed-loop control technique that regulates glucose levels and treats hyperglycemia and hypoglycemia employing continuous glucose, carbohydrate, and physiological variable data, as well as a hypoglycemia emergency alert module. Overall, the proposed scheme is effective in forecasting blood sugar levels within normal glycemic ranges, hypoglycemic ranges, and hyperglycemic values. Among 15 adults, a seven-day, day-and-night home inspection was conducted. The study commenced by tracking insulin sensitivity after meals were ingested, focusing next on how our technique responded to patients' physical activity. Precision (0.87), recall (0.87), $F$-score (0.82), delay (26.53), and error size (0.87) are used to assess performance $(1.14 \pm 2)$.

The study is organized into several sections, with the initial part being the introduction followed by Sec. 2, which describes related work. Section 3 outlines the proposed methodology of the work, Sec. 4 discusses experimental details and results, followed by Sec. 5, which details the conclusion and the future scope of the research.

## 2. Related works

Preventable medical errors (PME) are a major source of death worldwide. Wearable medical sensors (WMS) and clinical decision support systems (CDSS) work together and store patient details and provide case-specific suggestions; this system is called a health decision support system (HDSS) [15]. In [16], a raw database containing 150 156 patients provided by Basque Health Service, Spain, was used to conduct the study where 97% accuracy was achieved using SVM and LDA algorithms preliminary investigation based on the health status, identifying risk factors based on the health status, followed by providing appropriate treatment was conducted.

The robot employed is mainly used as a decision support system for diabetic children, offering support in terms of physical activity, bolus calculation, etc. [17]. This system sends a message to the patient to take medicine and triggers alarms for doctors and patients when there is an emergency [18]. The evaluation was conducted with a use of cases and human experts. A rule-based and ontology-enhanced recommendation system was used, and finally, the data were transferred to cloud storage for investigation and analysis [19].

For decision making, machine learning techniques such as fuzzy $c$-means clustering and $k$-means clustering have been used [20]. Additionally, the ECG signal has shown more promising results for noninvasive blood glucose measurements. Adolescents who received CGM optimization were more likely to experience a greater benefit and reduced burden from CGM.

In [21], the authors analyzed the efficacy of near-infrared methods, providing skin conductance measurement data under low blood sugar and euglycemic glucose clamping in 20 type 1 diabetes patients. The goal was to develop a multispectral system for hypoglycemic detection. Bio-sensor innovation for various physiological secretions, such as blood, perspiration, tissue fluids, optical liquid, as well as other physiological body fluids was examined to investigate the glucose levels. An overview of current CGM systems is presented to provide clinicians with guidance on how to initiate and use CGM in their practice settings.

## 3. Proposed methodology

We design a framework intended to monitor the blood glucose level of diabetic patients and give accurate guidance and support in terms of diet, insulin intake, exercise, etc., in a considerate manner. We use a CGM sensor for measuring the blood glucose level of the diabetic patient from the interstitial fluid to minimize the need for frequent finger pricking. Apart from CGM sensors, three more sensors are utilized to measure blood pressure, BMI, and heart rate due to their very close relationships. 6LowPAN is used to collect data such as blood glucose, blood pressure, heart rate, and BMI from sensor nodes to the smartphone. Finally, a push notification using MQTT is broadcasted to the physicians and patients to act in emergencies, if the level of blood glucose goes either too low or too high. Since the sensor nodes continuously generate a large amount of data, cloud computing techniques are used to store and analyze the data. Our proposed system is implemented on an energy-efficient sensor node. From the sensor nodes, raw data are transmitted to the fog layer through smart gateways.

Our proposed methodology focuses on the following two aspects:

- Remote monitoring of diabetic patients at home and managing different risk factors and emergencies.
- Storage of medical history and health records of the patients in the cloud for easy access by the medical practitioner at any given time and from any place.

We are going to deal with type 1 diabetes because it is a condition that cannot be cured but can be effectively kept under control through medication, proper diet, and physical activity. The monitoring of sugar levels is simplified, minimizing the burden on the patient.

### 3.1. Cloud-centric IoT-based model

We propose a cloud-centric IoT-based model for real-time patient monitoring. Here, data are stored on a cloud platform rather than on a computer hard disk. This allows easy access through an internet facility at any time and from any geographic location. We use the Microsoft Windows Azure cloud due to it ease deployment and application management. Here, raw data is collected in the .csv format and stored in the HDInsight cluster, then transformed using interactive queries and stored in the Azure SQL database using Apache Sqoop. Finally, Power BI is employed to perform analysis on the data stored in the cluster.

The service flow for diabetes patient care at home and hospital is depicted in Figs. 1 and 2. In the first stage, the patient's health conditions are assessed

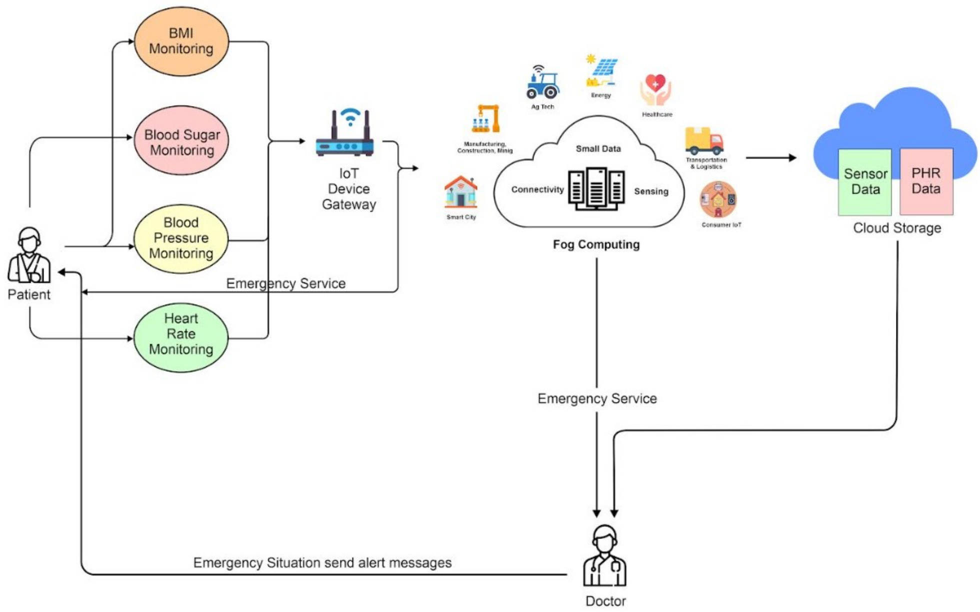


FIG. 1. Service flow diagram for diabetes patient care at home.

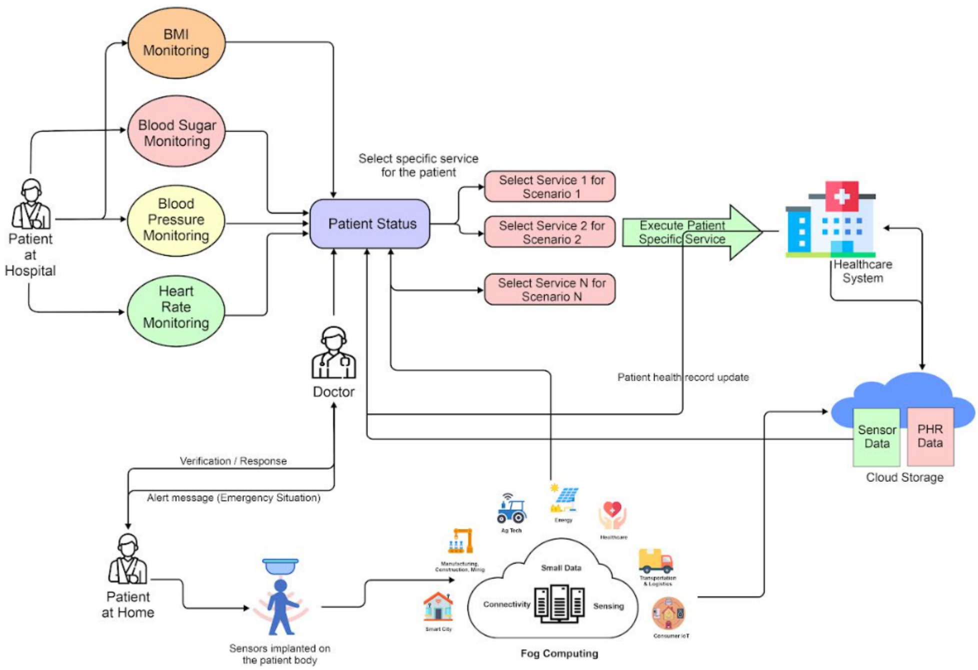


FIG. 2. Service flow diagrams for diabetes patient care at hospital and home.

and their statuses are recorded. Depending on the status of the patient, specific services are selected and executed by the healthcare system. In the second stage the patient's health conditions are monitored in the home environment with the help of an implanted medical sensor network (MSN) and treatment is provided when required by the physician. Before storing the data in the cloud for analysis and decision-making, it is preprocessed in the local database to avoid duplicate records, to fill in missing data, etc.

### 3.2. Data preprocessing

In the proposed system, the first stage is data preprocessing. Since the data are collected from various sensors in different time slots and it is in different formats, cleaning the data is mandatory to get more accurate results.

*3.2.1. Filling the missing values.* In every dataset, the common issue encountered is the missing value, and how this is handled is a big question mark for all the researchers. Many techniques have been presented in the literature review to deal with the missing data, but our work is to fill the missing value with the mean value of the column.

The normalization of data by the $z$-score technique is expressed as follows:

$$x = \frac{(x_i - \mu)}{\sigma}, \tag{1}$$

where $x_i$ is the observed value, $\mu$ refers to the mean value, $\sigma$ represents the standard deviation value, mean value is

$$\mu = \frac{\sum\limits_{i=1}^{n} x_i}{n}, \tag{2}$$

let us assume $n$ refers to the number of data points, standard deviation is

$$\sigma = \sqrt{\frac{\sum (x_i - \overline{x})}{n-1}}. \tag{3}$$

*3.2.2. Feature extraction.* After filling the missing value, important, non-redundant, and independent data elements must be extracted from the dataset using the derivative method, since sensors continuously generate redundant data. The derivative is computed using the following formula:

$$g'(y_i) = \frac{(g(y_{i+1}) - g(y_i))}{(y_{i+1} - y_i)}, \tag{4}$$

where $g(y_{i+1})$ and $g(y_i)$ represent the sensor values at $y_{i+1}$ and $y_i$, respectively.

*3.2.3. Feature selection.* Identifying the subset of data that is best suitable for the final prediction also improves prediction performance. An unsupervised clustering-based technique like the $k$-means clustering technique is implemented in the fog layer for feature selection. This technique finds highly correlated data from complex datasets. The $k$-means clustering algorithm is used to group the data objects based on the Euclidean distance $D$ between the cluster centroid $(c_1, ..., c_k)$ and data objects $(x_1, ..., x_n)$. Initially, cluster centers are selected randomly; then, based on the Euclidean distance between the centroid and data points, data points are added to the cluster if they exhibit the minimum distance from all other clusters.

**Algorithm 1.** $k$-means clustering algorithm

| | |
|---|---|
| **Input**: | $N$ number of data objects $(x_1, ..., x_n)$ |
| **Output**: | $k$ number cluster centroids $(c_1, ..., c_k)$ |
| **Initialization**: | from $N$ the number of data objects $(x_1, ..., x_n)$ choose a set of cluster centroids randomly |
| **Step 1**: | **begin** |
| **Step 2**: | **repeat** until converged |
| **Step 3**: | **for** every data object $n \in N$ |
| **Step 4**: | **for** every cluster centroid $k \in K$ |
| Measure the Euclidean distance among the cluster centroids and data objects. | |
| **Step 5**: | **end for** |
| **Step 6**: | According to the minimum Euclidean distance, assign all data objects $N$ to cluster centroid $K$ |
| | **end for** |
| **Step 7**: | **for** every cluster of centroid $K$ |
| Calculate the average weights of each cluster centroid $1, ..., k$ | |
| **Step 8**: | **end for** |
| **Step 9**: | **end repeat** |
| **Step 10**: | **end** |

*3.2.4. Estimation of insulin infusion rate from blood glucose concentration using time-varying state model and extended Kalman filter.* At time $t$, let $Ø'(t)$ denote the measured blood glucose level, $x'(t)$ denotes the insulin supplied, $y'(t)$ is the carbohydrate consumed, and $z(t)$ denotes the energy consumed due to physical activity at time $t$.

Measured blood glucose level at time $t$:

$$\phi'(t) = \sigma(t) + n_1(t), \tag{5}$$

where $\sigma(t)$ is the glucose concentration in the interstitial fluid and $n_1(t)$ is the measurement noise.

Measured glucose concentration in the interstitial fluid at time $t+1$:

$$\sigma(t+1) = \mu_t\left[\sigma(t)\right] + I_t\left[X(t-u)\right] + M_t\left[X(t-v)\right] + \beta(t), \tag{6}$$

where $\mu_t\left[\sigma(t)\right]$ is the autoregressive value denoting the blood glucose values at time $t+1$, $I_t\left[X(t-u)\right]$ is the dynamic linear regression of blood glucose values at time $t+1$ after insulin delivery with $u$ delay, $M_t\left[X(t-v)\right]$ is the dynamic linear regression of blood glucose values at time $t+1$ after meal intake with $v$ delay, and $\beta(t)$ is the process noise:

$$\mu_t\left[\sigma(t)\right] = \tau_1(t)\,\sigma(t) + \tau_2(t)\,\sigma(t-1) + \ldots + \tau_n(t)\sigma(t-n-1), \tag{7}$$

$$\begin{aligned} I_t\left[x(t-u)\right] = {} & \phi_1(t)\,X(t-u) + \phi_2(t)\,X(t-u-1) + \ldots \\ & + \phi_n(t)X(t-u-(n-1)), \end{aligned} \tag{8}$$

$$\begin{aligned} M_t\left[X(t-v)\right] = {} & \theta_1(t)\,X(t-v) + \theta_2(t)\,X(t-v-1) + \ldots \\ & + \theta_n(t)X(t-v-(n-1)), \end{aligned} \tag{9}$$

where $\tau_k(t)$ is the autoregressive coefficients, $\varphi_n(t)$ and $\theta_n(t)$ are the linear regression coefficients that are time-varying coefficients. $\varphi_n$ can be considered negative because insulin intake always decreases the blood glucose concentration level, whereas $\theta_n$ can be assumed to be positive, as carbohydrates always increase the blood glucose concentration level.

The time delay between insulin delivered and absorbed in glucose is:

$$\begin{aligned} x'(t) = {} & s(d)x^1(t-d) + s(d+1)x^2(t-d-1) + \ldots \\ & + s(d+n)x^n(t-d-n \rightarrow), \end{aligned} \tag{10}$$

where $d$ is the dead time of $t$ intervals.

*3.2.5. Glucose prediction based on meal.* Let $M_{\mathrm{st}}$ be the meal start time, $M_{\mathrm{et}}$ be the meal end time, $M_{\mathrm{cg}}$ is the meal carbohydrate in terms of grams, and $M_{\mathrm{d}}$ is the meal duration. Then, the meal can be defined as $M = [M_{\mathrm{st}}, M_{\mathrm{et}}, M_{\mathrm{cg}}, M_{\mathrm{d}}]$. The maximum meal time is considered as $M_{\mathrm{m}}$ and the maximum meal size is $M_{\mathrm{max}}$, the maximum delay $M_{\mathrm{d}}$ that occurs between the meal consumption and blood glucose diverging into the blood is $M_{\mathrm{d}} - M_{\mathrm{st}}$.

The experiment will then be repeated for the entire day, with varying meal start times, maximum meal sizes, and delays. The projected rise in glucose content $G'$ after meal consumption is compared to the observed glucose $G''$. The rate of glucose production at time $t$ is associated with the rate of carbohydrate consumption during the meal, where $G'(t)$ is the rate of glucose and $y'(t)$ is the rate of carbohydrate consumption:

$$\left(G'\left[t'-t\right]\right)' - \left(G''\left[t'-t\right]\right)' > \psi, \tag{11}$$

$$d_{\mathrm{Euc}} = \sqrt{\sum_{i}^{t} \frac{\left|G'(i) - G''(i)\right|^2}{t - M_{\mathrm{st}}}}, \tag{12}$$

where $d_{\mathrm{Euc}}$ is Euclidian distance.

Carbohydrate level at time $t$ is measured by:

$$y'(t) = \sum_{t=1}^{n} d_{\mathrm{Euc}}(t) + d_{\mathrm{Euc}}(t-1) + ... + d_{\mathrm{Euc}}(t-n-1). \tag{13}$$

Using this formula, calculate the insulin dose by carbohydrate coverage:

Carbohydrate (CHO) insulin dose = total CHO grams in the meal/CHO in grams inclined by 1 unit of insulin:

$$I_{\mathrm{CHO}} = \frac{y'(t)}{\mathrm{CHO}}, \tag{14}$$

where CHO in grams inclined by 1 unit of insulin differs based on the total daily insulin dose per day.

Let $\psi(t)$ represent the collection of all autoregressive and linear regressive terms:

$$\psi(t) = \left[\tau_1(t), ..., \tau_n(t), \varphi_1(t), ..., \varphi_n(t), \theta_1(t), ..., \theta_n(t)\right]^T, \tag{15}$$

$$\psi(t+1) = \psi(t) + N(t) + I_{\mathrm{CHO}} + x'(t), \tag{16}$$

where $N(t)$ is the noise.

Based on the $\psi(t+1)$ values, the insulin amount to be taken at any particular moment will be measured and sent to the patient and caretaker.

*3.2.6. Measuring energy expenditure based on physical activity.* Physical activity (PA) is a complex behavior that is difficult to accurately assess, in part due to its multiple dimensions. Physical exercise energy expenditure (EEE) is a component of total body energy expenditure (TBEE). TBEE is typically divided into three factors: the main component is the resting metabolic rate (RMR), diet-induced energy expenditure (DIEE), and energy expenditure as a result of physical or muscular activity (EEE). RMR denotes the sum of energy required to maintain temperature and involuntary muscle reduction. Among the accelerometers currently in use are piezoelectric sensors, which can detect the number of accelerations in all three planes.

Physical activity energy expenditure (PAEE) is calculated as:

$$\text{PAEE} = \frac{\text{TDEE}}{\text{body weight}} - \text{RMR} - \text{DIT},$$

where TDEE – total daily energy expenditure, RMR – resting metabolic rate, DIT – diet-induced thermogenesis, and TDEE is calculated as:

$$\text{TDEE} = \frac{\sum_{t=1}^{n} py(t) + py(t-1) + \ldots + py(t-n-1)}{n} * 100\%,$$

where $py(t)$ is energy expenditure due to physical activities at time $t$.

Based on the PAEE value, the calculated insulin amount will be adjusted.

When blood glucose levels drop below the given threshold (4 mmol/L or 72 mg/dL), a problem arises. Hyperglycemia is defined as a blood glucose level of more than 125 mg/dL, which can cause damage to the heart, kidneys, eyes, nervous system, and other major life-threatening consequences.

Sudden Hypoglycemia (SH) has also been linked to heart problems, including arrhythmias. ECG monitoring during controlled daytime hypoglycemia has been recommended as a way to examine the impact of nocturnal hypoglycemia on cardiac arrhythmia and the 'dead in bed' phenomenon. Fear of hypoglycemia is a well-known impediment to effective glucose regulation.

*3.2.7. Apriori algorithm.* We use an association rule mining Apriori, a machine-learning algorithm, to discover patterns from variables, following associations to define association rules:

$$\text{Support} = \frac{Freq(X,Y)}{N}, \tag{17}$$

$$\text{Confidence} = \frac{Freq(X,Y)}{Freq(X)}, \tag{18}$$

where $Freq(X,Y)$ is frequently bought items, $Freq(X)$ is the number times $X$ occurs, and $N$ is the total itemset.

*3.2.8. Power consumption by 6LoWPAN devices.* The 6LoWPAN protocol allows real-time diabetes devices based on the 802.15.4 wireless sensor network standard to communicate with IPv6 while consuming less power. 6LoWPAN devices have a data rate of 250 kbps and a frame size of 127 bytes, which would

**Algorithm 2.** First-level decision using blood glucose measure.

Begin:

If the implanted sensors model is active,

a. Send the data through a gateway to the local system (fog)
   - Within the local system, preprocessing is done to avoid duplicated data, fill in missing data, etc.
     - After the preprocessing steps, the data are deposited in the cloud for further analysis.
       - In the analysis phase, based on inputs received from the implanted sensors model, the amount of insulin to be taken and at what time it should be taken will be decided and conveyed to the patient's mobile as an alert message.

b. If the glucose level of the patients is in the normal range
   - Stop the process
     - Else if the glucose level ranges from 150–180 mg/dl, send an alert message to the caretaker or patient to take the prescribed insulin.
     - Else if the glucose level is 180 mg/dl and above, the model will send a high alert to the doctors/nurse station to take immediate action.

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**Algorithm 3.** Based on blood glucose level, blood pressure rate, and heart rate.

Begin:

If the blood glucose level is high and the blood pressure rate is high, or the heart rate is low

- The patient is at high risk, immediately report to the doctor

  Else if the blood glucose level is very low or heart rate is very high
  - Emergency – send an alert message to the doctor.

  Else if the blood glucose level is low or the heart rate is high
  - Start the diet, stop the physical activity for 30 minutes, and increase the insulin intake prescribed by the model.

  Else if the blood glucose level is high or the heart rate is low
  - Stop activities and start the diet.

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necessitate a lot of comparison to control most automation devices using IPv6. Our gateway may operate as a bridge or a router and provides a 6LoWPAN adaption layer, 6LoWPAN-ND, and IPv6 RPL routing to use a standard IPv6 protocol stack with a 6LoWPAN wireless interface. In this mode, the gateway creates a virtual second interface for packet filtering.

This test bed's 6LoWPAN node is built on a TI CC2530 application board, and the application boards run Contiki. It includes an 8051 MCU, 256 KB of programmable flash memory, a 2.4 GHz RF transceiver, 8 KB of RAM, batteries, and a power source. The typical current consumption of this sensor is

70 A in normal operation, and when powered off, the power consumption is less than 0.3 A.

As we all know, power management is critical for real-time systems that have a long-life span. The gateway is always linked to a USB port in our approach; therefore, no batteries are required. However, as previously mentioned, our 6LoWPAN devices centered on the TI CC2530 require a power source like batteries.

Average current consumption is determined by:

$$CC_{\text{avg}} = \sum_{i=0}^{n}\left(\frac{C_i}{D_i} * CC_i\right) + \left(1 - \sum_{i=0}^{n}\left(\frac{C_i}{D_i}\right)\right) * C_{\text{sleep}}, \tag{19}$$

where $C_i$ is the time at which the device utilizes the average current $CC_i$, $D_i$ is the aggregate duration during which the average consumption is determined, $C_{\text{sleep}}$ is currently consumed during sleep mode, and $CC_{\text{avg}}$ is the average current consumption for the total duration $D_i$.

## 4. Experiments and results

### 4.1. Dataset

We use the OhioT1DM dataset for our research work and it contains 20 columns as follows: Patient ID, glucose level measurements from CGM sensors, blood glucose level from a finger stick, basal temp, basal bolus, meal, sleep, work, stressors, hypo event, illness, exercise, basal heart rate, basal GSR, basal skin temperature, basal air temperature, basal step, basal sleep, and acceleration. This dataset contains data about 12 type 1 diabetes patients for an 8-weeks period. It is divided into an 80–20 split rule for training and test data.

### 4.2. Representation of data

Figure 3 provides a graphical representation of the data that is being collected and stored in the cloud.

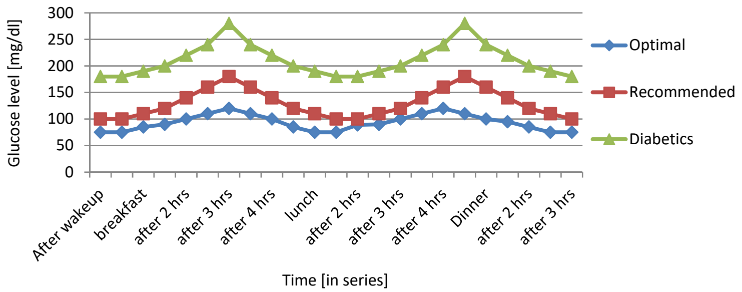


Fig. 3. Blood glucose level chart.

### 4.3. Bolus insulin predictor

If one uses basal insulin, the insulin dose does not change. One can take the same amount of insulin regardless of, the blood glucose level. However, bolus insulin depends on the blood sugar level before the meal or during bedtime. Pre-mixed insulin doses depend on the blood sugar level before mealtime.

Table 1 illustrates the exact units of insulin to be consumed in the morning, afternoon, and night. This is based on the parameters, including patient age, and carbohydrate intake, past and current blood glucose level, and intensity and duration of physical activities.

TABLE 1. Insulin table.

| Patient ID | Patient age | Carbo-hydrates level [g] | Blood glucose level [mg/dl] | Action needed | Physical activity energy expenditure (PAEE) | Insulin [units] | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Morning | Afternoon | Night |
| PID 1 | 40 | 15 | <90 | Depending on the weight, consume 15–30 g of carbohydrates | Less than 30 minutes | NA | NA | NA |
| PID 2 | 40 | 15 | 90–161 | Depending on the insulin, physical activity, and weight consume 10–20 g of carbohydrates | Low to moderate intensity activities for less than 1 hour | 1 | 1 | 1 |
| PID 3 | 40 | 15 | 160–220 | Do not consume carbohydrates, start an exercise | Moderate to high-intensity exercise for 1 hour until BG comes down to 150 | 2 | 2 | 2 |
| PID 4 | 40 | 20 | 221–280 | Do exercise with low-moderate intensity | Low to moderate-intensity exercise until BG comes down to 250 | 4 | 4 | 4 |
| PID 5 | 40 | 25 | 281–340 | Check ketones and stop exercise for high concentrations, else do exercise with low-moderate intensity | Do not exercise | 6 | 6 | 6 |
| PID 6 | 40 | 30 | 441–400 | Check ketones and stop exercise for high concentrations, adjust the insulin value up to 50% | Do not exercise | 8 | 8 | 8 |

Figure 4 illustrates the system response time for varying data size, and it clearly indicates that response time increases as the number of patients increases. Compared to an existing system, our system response time is much lower as the data expands.

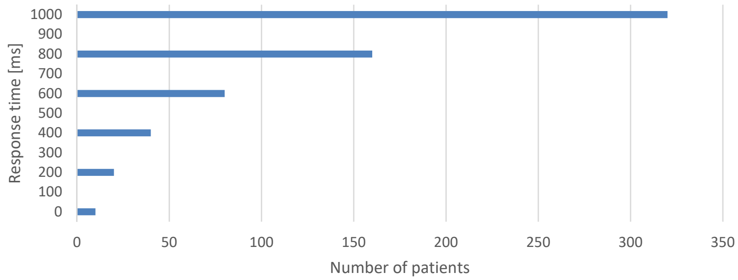


FIG. 4. Performance of the proposed system with varying data size.

Table 2 details the rules formulated by the association rule mining Apriori algorithm. For each rule, the percentage of coverage and confidence level obtained is given. These rules establish correlations among the following key metrics: blood glucose (BG), blood pressure (BP), heart rate (HR), age, and BMI. The confidence level change for different combinations of the above metrics is shown in the above table. Here, support or coverage indicates that when

TABLE 2. Rules formulated by the association rule mining Apriori algorithm.

| S. No. | Rules | Coverage | Confidence [%] |
|---|---|---|---|
| 1 | If BG = high and BP = high and HR = low and age >45 and BMI = high | 75 | 99 |
| 2 | If BG = high and BP = high and HR = low and age <45 and BMI = low | 68 | 98 |
| 3 | If BG = high and BP = low and HR = low and age >45 and BMI = low | 110 | 96 |
| 4 | If BG = high and BP = low and HR = high and age >45 and BMI = low | 64 | 97 |
| 5 | If BG = low and BP = low and HR = low and age >45 and BMI = low | 150 | 96 |
| 6 | If BG = low and BP = high and HR = high and age >45 and BMI = low | 87 | 98 |
| 7 | If BG = low and BP = high and HR = low and age <45 and BMI = high | 130 | 95 |
| 8 | If BG = medium and BP = normal and HR = normal and age <45 and BMI = low | 180 | 98 |
| 9 | If BG = medium and BP = normal and HR = normal and age >45 and BMI = high | 143 | 95 |

blood pressure increases or decreases, BP and HR may also increase or decrease simultaneously. Confidence reflects the changes in blood pressure and heart rate when one increases or decreases.

Table 3 provides simulated results of 350 samples for the whole day. The error rate $E_i$ denotes the error size in carbohydrate content in grams, while the delay represents the time gap between meal consumption time and detection time.

TABLE 3. Measure of precision, recall, $F$-score, delay, and error rate.

| Experiment | Precision | Recall | $F$-score | Delay [min] | Error rate |
|---|---|---|---|---|---|
| Breakfast | 0.94 | 0.93 | 0.94 | $25.6 \pm 3$ | $0.7 \pm 2$ |
| Post breakfast | 0.90 | 0.91 | 0.92 | $27.1 \pm 2$ | $0.9 \pm 4$ |
| Lunch | 0.88 | 0.87 | 0.86 | $27.2 \pm 2$ | $1.2 \pm 3$ |
| Post lunch | 0.85 | 0.83 | 0.84 | $26.9 \pm 3$ | $1.4 \pm 2$ |
| Dinner | 0.80 | 0.81 | 0.82 | $25.7 \pm 1$ | $1.5 \pm 3$ |
| Overall | 0.87 | 0.87 | 0.82 | $26.5 \pm 3$ | $1.14 \pm 2$ |

Evaluating fault data in a network environment poses challenges in the data prediction failure analysis. This proposed failure rate analysis is compared with the existing method, as shown in Fig. 5. The analysis of the proposed IoT-DPHM results shows that the proposed method records a failure rate of 11.5% or less, an improved performance compared to other methods, such as existing PSRWT and LS-IoT methods with higher failure rates.

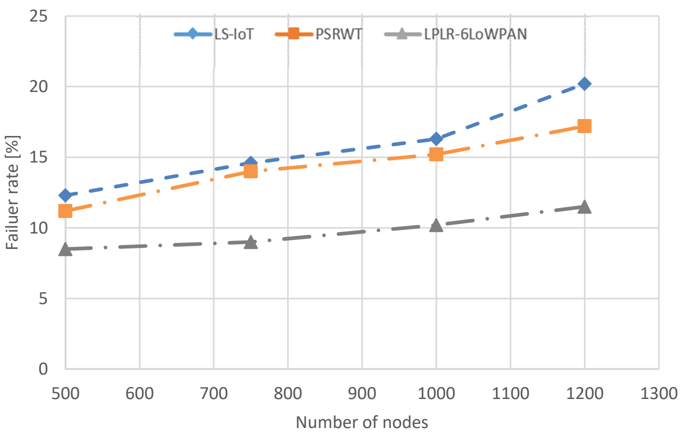


FIG. 5. Failure rate analyses.

We created a closed-loop control system that uses continuous glucose, carbohydrate, and physiological variable data to regulate glucose levels and treat hyperglycemia and hypoglycemia, as well as a hypoglycemia early warning module. The simulator's default sample time is one minute, but we have set a 5-minute sampling time. Overall, the proposed models demonstrate proficiency in predicting blood sugar levels within the normal glycemic range from >70 to 180 mg/dl, hypoglycemic value <70 mg/dl, and hyperglycemic value of 180 mg/dl. We undertook a first seven-day, day-and-night home study among 15 adults. In the closed-loop therapy, a considerably higher percentage of time was spent within the target blood glucose range compared to sensor-enhanced pump therapy (67 [51, 69] vs. 52 [43, 60] percent, median [IQR], and $p = 0.005$). During closed-loop, the mean glucose value was 7.9 vs. 8.0 mmol/l, $p = 0.026$, and the time spent beyond the target $p = 0.014$ was reduced, whereas the time spent below the target ($p = 0.339$) was comparable. During both the day $p = 0.018$ and night $p = 0.012$, participants spent more time in the target.

## 5. Conclusion and future scope

Based on food consumption, physical activity, and blood glucose level, the suitable amount of insulin intake and the appropriate time for its consumption can be suggested to patients. In older patients with type 1 diabetes, strategies to reduce meal-stimulated hyperglycemia during the day and prevent hypoglycemia at night are important clinical goals. We implemented a low-cost real-time health monitoring system to continuously monitor blood glucose levels and offer analysis and real-time notifications for instant response. We first started by checking insulin levels after meal consumption and later concentrated on how our system reacted to the physical activity of the patients. Evaluation is conducted based on performance parameters such as precision (0.87), recall (0.87), $F$-score (0.82), delay ($26.5 \pm 3$) and error size ($1.14 \pm 2$).

We discovered that continuous glucose monitoring was more effective than self-monitoring of blood glucose in managing type 1 diabetes based on moderate certainty in the evidence. Our proposed system results can benefit people with T1D by reducing their burden of multiple daily finger sticks when using CGM and can enhance the cost-effectiveness of CGM therapy by reducing the number of daily BGM test strips. Furthermore, based on the evidence that insulin dosing based on CGM, carbohydrates, and physical activity is safer than intricate artificial pancreas systems that automatically deliver insulin based on only CGM sensor glucose measurements.

In the future, we intend to predict insulin infusion rate by using a greater number of parameters and implement the system in a wider group of people, and also to improve the performance of the system.

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