A Predictive Modeling Engine Using Neural Networks:

Diabetes Management from Sensor and Activity Data

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Abstract— **Diabetes is a common but serious chronic disease. Nearly 8% of Americans who are aged 65 and older (about 10.9 million) suffer from this deadly disease. Self-management of this disease is possible, yet the older population lack knowledge, have denial and often lack motivation to do so. Recently we have demonstrated sensor-based network architecture within the home to monitor daily activities and biological vital parameters [25]. The data is mined to find patterns and abnormal values. Through daily text messages that are sent to the subjects, we have achieved to influence behavior change using persuasive principles. In this paper, we analyze the daily data and demonstrate that a model to profile the subject's daily behavior is possible using Artificial Neural Networks (ANN). Such a profiling has the advantage of knowing the situations, when the subject's daily activity deviates from its "normal profile", which may be a possible indication of an onset of some health condition or disease. Lastly we develop an ANN based model to predict blood sugar level based on previous day's activity and diet in-take. Such a model can be used to help a subject with high blood sugar to adjust daily activity to reach a target blood sugar level and also gives a care-giver advance notice to intervene in adverse situations.**

Keywords- Diabetes, sensor networks, persuasive technology, texting, neural networks, healthcare modeling, prediction

I. INTRODUCTION

Diabetes mellitus is the most common and serious chronic disease facing the entire global population. In the United States, there are nearly 26 million Americans with diabetes, 30% of which are aged 65 and older [1]. California in particular has the highest incidence of new diabetes cases and nearly 4 million people estimated to be suffering from the disease [2]. The costs of caring for this disease are astronomical and are estimated to exceed more than $24 billion in California and $174 billion nationally [1, 2]. Diabetes remains a major health problem being responsible for up to 8% of national health care expenditure.

Diabetes is a chronic disease characterized by a sustained elevated blood glucose level, caused by a reduction in the action of insulin secretion where related metabolic disturbances generate severe, acute and long-term complications that are responsible for premature death and disability [10]. The World Health Organization projects that diabetes deaths will increase by more than 50% in the next ten years without urgent action. Most notably, diabetes deaths are projected to increase by over 80% in low-middle income countries between 2006 and 2015 [18].

Despite the availability of effective treatment, diabetes remains poorly controlled. Fewer than 7% of diabetic patients meet treatment goals for lipids, blood pressure, and glycosylated hemoglobin A1C [3, 4]. Elderly patients with diabetes have higher rates of mortality, congestive heart failure, myocardial infarction and stroke as compared to age-matched controls without the disease [5]. Moreover, despite evidence that the mortality rate is decreasing over time, the rate of complications is remaining the same [6]. As a result, the average number of lifetime complications per patient is increasing as patients are living longer. With the incidence of diabetes rapidly rising, this is a fatal combination for the economic wellbeing of our health system.

Diabetic patients need to self-manage the disease diligently. Poor adherence to recommended self-management guidelines is well-recognized as a significant barrier to effective glycemic control. Improved outcomes have been associated with better adherence to medications, blood sugar self-monitoring, diet and lifestyle changes, and appointment attendance [7 - 9]. Barriers include time constraints, knowledge deficits, denial, limited social support, inadequate resources, and low self-efficacy.

Many of the older adults have difficulty achieving tight control because of the high degree of cognitive resources needed to manage diabetes. With age, one has weak problem solving skills, they often forget and daily management becomes a chore [26]. A major challenge in chronic disease self-management, particularly in older Americans, is social isolation [15]. Elderly diabetic patients with poor social support have twice the mortality rate of those with adequate support [16]. Studies consistently show that patients with empowered caregivers or peers have better outcomes [16].

Using information technology and wireless sensor networks within the home, diabetic patients can be assisted. A promising approach is to remotely monitor activity of daily living (ADL) [14, 19]. Such data if mined properly can identify health patterns which can then be used to send effective reminders and feedback [13, 18]. Mobile phones are an ideal platform for sending feedback to diabetes patients because they are ubiquitous, low-cost, reliable, real-time, and versatile; and unlike most technologies, actually enjoy greater usage amongst racial/ethnic minorities. Younger patients definitely benefit from using a mobile phone but even older adults are getting used to smartphones with slightly bigger displays [11, 12].

We have recently implemented a mobile wireless sensor-network monitoring system within the homes which we call "persuasive sensing technology". We have reported significant outcome and positive results in a recent paper [25]. Here we briefly describe our "persuasive technologies" implementation, which are applications and devices intentionally designed to change user behavior [20-23]. In this paper, we present new results obtained from mining ADL data using machine learning algorithms with Artificial Neural Networks (ANN). We call this the predictive modeling engine. In fact our models can now predict certain biological and physiological parameters 24 hour in advance with relatively high accuracy. This paper discusses the details and results of our predictive modeling engine using ANN.

II. System Architecture and Prototype

Any at-home healthcare solution must detect and respond to the activities and/or characteristics of the older person. A network of sensors (worn, carried, or environmental) is an ideal technology platform for detecting and responding to health-relevant parameters such as movement, sleep, weight, physiological data and social activity [14]. A WSN device is a packaged data collecting or actuating component, which includes a sensor and/or actuator, a radio stack, an enclosure, an embedded processor, and a power delivery mechanism [14]. The sensor interacts with the environment and sends an appropriate signal (analog or digital) to the embedded processor (also called microcontroller unit). We used Iris Mote technology developed by Intel and UC Berkeley labs. The mote hardware platform consists of a microprocessor and radio chip (MPR). Sensors connect directly to the mote processor radio boards via various interfaces. This combination gives the mote the ability to sense, compute and communicate. The mote enables raw data collected by the sensors to be analyzed in various ways before sending it to an aggregator (in our case a laptop) that we placed within the home. The aggregator then uploads daily activity data to the cloud through se- cured channels via the Internet. The following different types of sensors were implemented in this project:

Ambient Sensors: A simple on/off switch that detects open/close of garage door (through which subjects leaves homes), detects the back porch door for outdoor access. An infra-red analog sensor was used to detect presence in the bedroom. A pressure pad sensor (from Colonial Medical) was placed in the couch in the living room in front of TV. Simple on/off switches were used to detect opening and closing of medication cabinet and the cabinet containing insulin. A photo sensor was connected to the TV to detect television viewing.

Device-level sensors: A blood glucose monitor device was chosen that can connect easily to the laptop via USB and can upload BG values daily. A wireless weight machine (from Tanita Corporation) that sends value via Bluetooth was placed in the family room.

Body-wearable sensor: A commercial body-wearable sensor from BodyMedia Inc. which is an arm-band was given to the patient to wear 24 hours. This multi-sensor senses number of steps walked, quality of sleep, and many other physiological parameters such as skin temperature. Data is uploaded to the cloud by connecting it to USB port for five minutes daily.

Two subjects were shown how to log into BodyMedia website where s/he could input diet/nutrition information. Our system would then fetch daily diet data and we could then compute total calories consumed. We also provided the patient with bottled water and asked him to only drink that during the course of the experiment. This was a simple way for us to monitor water intake.

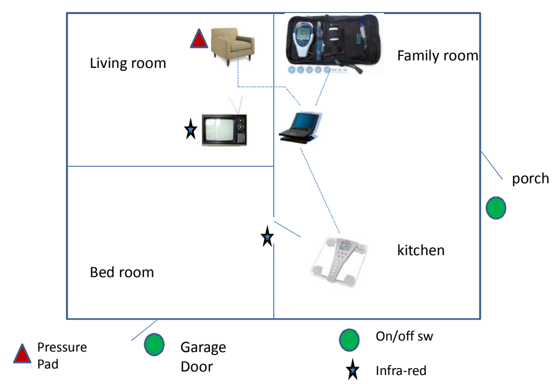

Figure 1: Sensor placement within the home

The overall architecture schematic is shown in Fig. 1. The on/off switches were not wireless, so we had to run wires from them to the microcontroller. We originally had plans to sense the kitchen microwave and refrigerator usage also. But as the long wires would disturb the subject's beautification of the kitchen, we abandoned that idea.

III. Intervention and Results

A. Intervention and subject recruiting

Our **intervention** has two components.

- System sends daily text/SMS on cell phone. They are tailored messages targeting behavior change.
- A tailored newsletter that summarizes healthy living parameters is presented to subject once a week and is jointly read by family member or one of our research team members.

Note our intervention (through the prototype persuasive sensing system) is aimed to engage patients in diabetes self-management through interactive SMS and newsletter approaches. It was important to ensure that daily text messages sent to the subject were fresh and relevant. Each day the subjects received up to 3 text messages that were delivered to them over an LG smart phone and an iPhone. Below we show an example of how messages were varied for physical activity (Tables 1). The physical activity is measured by the number of steps obtained from the Bodymedia sensor.

Case	**Steps >= 8000**	**Steps < 8000**
Mon	Great Job! Keep up the good work.	Don't give up on physical activity. Try walking a mile each day.
Tue	You have exceeded your goal. Congratulations.	Don't give up physical activity. Have you taken the stairs?
Wed	You are doing very well. Keep it up!	Have you reached your goal of 8000 steps?
Thu	You are a super hero. You have exceeded your goal.	You fell short of your goal. Don't worry. Try to walk a mile after dinner.
Fri	You have exceeded your goal. Super job!	Never say never. You can do it.
Sat	Steps graph for past 5 days	Try some brisk when you are in the parking lot.
Sun	Great Job. Enjoy the Sunday with friends and family.	It is a beautiful day. Go out and do brisk walking for 30 mins.

Table 1. Messaging algorithm for physical activity

Similar daily text messages were sent for calorie intake, blood-glucose measurement values and sedentary activity.

We obtained approval from our university Institutional Review Board (IRB). The first subject is an 82 year old white male who is retired and lives in the Vista community near San Diego. He has type 2 diabetes, and also a few other health problems. He agreed to the consent form and we started our project implementation. The second subject is a 60-year old white female who is obese, suffers from Type 2 diabetes and is considered a high-risk patient as her BG values are very high. She is very technology savvy and carries an iPhone to conduct most of her work.

B. Results Summary

Experimental results have been recently reported in a paper [25]. Here we provide detailed summary statistics (maximum, minimum, mean and standard deviation) of different parameters for both subjects as shown in Table 2 (see at end).

In Figure 6, we have plotted the variation of blood glucose (BG) level, weight, idle time and number of steps walked per day by each subject throughout the experiment duration. Figure 6A demonstrates that there is a downward trend on BG level for both subjects. The weight (Figure 6B) is also in the downward trend, but absolute amount of weight reduction is not that significant. This is most likely because drastic reduction of weight within such short experiment duration is not possible. However, the downward trend of weight should encourage running such experiment for longer duration in future to potentially observe significant reduction in weight. The idle time spent by both the subject during the experiment has seen a dramatic downward trend. The number of steps taken per day has an increasing trend for both the subject, throughout the experiment duration.

HbA1c is a lab test that shows the average amount of sugar in your blood over the past 3 months. It is a reflection of how well a patient is controlling their diabetes. An HbA1c of ^% or less is normal. We studied pre and post intervention results of HbA1c. For subject #1, pre-experiment HbA1c was 12.9% but post-experiment it came down to 6.6%. This is a significant improvement which proves our main hypothesis that our system can lead to better outcomes. For subject #2, the pre and post HbA1c values were 8.9% to 8.5%. This may not be as much as subject #1 but still an improvement. Keep in mind that subject #2 was considered high-risk.

Next, we intend to find the impact of daily activity level on the BG level of two subjects. For this first we decided to do statistical analysis. However, the various data collected in our experiment are not independent, so we cannot run a multi-variate regression analysis to statistically conclude anything. Additionally the number of data points (rows) is small to draw any general conclusion from the data items. However, we ran several univariate and bivariate regression analysis to see if heuristically we can see evidence on the dependency of BG level on daily activity levels. We found that for subject 1, BG level is highly correlated with weight and idle-time, both of which are related to the daily activity of the subject (Table 7). We also found for subject 2, the BG level is highly correlated with number of steps taken and the total in-out count, which are related to the daily activity of the subject. The detail of this regression analysis is presented in Table 7. We would like to highlight here that such statistical analysis cannot give us any concrete conclusion but heuristically we could say BG level is dependent on the daily activity level of the subject. Actually, the BG level is non-linearly dependent on many different data items that the experiment has collected such as calorie intake, activity and sleep efficiency. In section VII, we model the BG level using an artificial neural network technique (ANN) and present some analysis on how well we can model and predict the BG level of a subject.

IV. PROFILE BUILDING USING MACHINE LEARNING AND NEURAL NETWORKS

In this section we explain and demonstrate an approach for health behavior profiling applying machine learning techniques to human behavior data captured by sensors described before. Some of the key challenges in developing such profiling are as follows.

i. The sensor data may have some inaccuracy.
ii. The daily behavior pattern of a human may not be exactly the same
iii. There may be some deviation in the daily routine activities due to unexpected scenarios such as but not limited to guest's arrival at home, and some urgency in family.

We need to develop an approach that addresses these situations but still be able to model human behavior that can be used for disease profiling.

Fundamentally we have relied on Replicator Neural Network (RNN) [9] to model human behavior. Traditionally RNN has been used for anomaly and outlier detection. Following this, once the RNN is trained with the training behavioral data of a subject, the RNN can be used to detect whether any future behavior of that human subject matches with the trained profile or not.

One of the key characteristics of a RNN is that the input and outputs are same. In our scenario, we have used daily human behavior data (such as number of steps, hours of sleep, time in couch, time in watching TV, number of times went outside) as both the input and output. The ANN is trained based on the same input and output. During testing, the Mean Square Error (MSE) between the input and output is taken as the indication of whether the test input data follows the pattern derived from the training input data.

One of the challenges in feeding the data of daily behavior into RNN is that, the data may have some anomalies due to reasons not related to our research and which are out of our control (such as visitor in subject's home, or long absence from home due to social visit or due to issues related to sensors). The first step in building the profile data is to identify the data points that represent the normal behavior of the subject. For this we applied K-mean clustering technique on the daily behavioral data of the subject. The data points related to the largest cluster in the K-mean output is taken as the routine daily behavior of the subjects. This daily behavior data is then fed into RNN as both input and output to train the RNN. Figs. 2 and 3 depict the process.

Figure 2: Building RNN model for disease profile

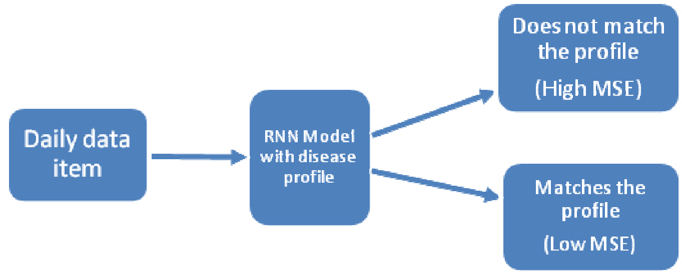

Figure 3: Using RNN model for disease identification

We collected the daily behavior data of two subjects (marked as subject 1 and subject 2) over the course of 21 days and 30 days respectively. The data included – (i) weight (ii) blood glucose (iii) number of steps taken (iv) quality of sleep (v) total minutes lied down (vi) total sleep time (vii) Total calorie in-take (viii) bed room time (ix) couch time (x) TV time and (xi) total number of in and out of the house. These data items were computed on a daily basis from the raw sensor data received. Thus the data had 11 columns, one for each data item. For subject 1, we had 21 rows and for subject 2, we had 30 rows (one row per day per subject).

We first applied K-clustering algorithm on the data set of each subject. For both subjects, the clustering resulted in only one cluster, indicating that there were no outlier data rows present in the data-set of each subject. For each subject, we identified the first 14 days (2 weeks) of data as the **training data** and the rest of the data as the **testing data**. Thus for subject 1 we had 7 days of testing data and for subject 2 we had 16 days of testing data. Each data points in both the training and testing data set had 11 fields as described before.

The training data set is then fed into the RNN with 11 input variables, 11 output variables and 2 hidden layers each with 8 neurons. Typically the configuration of neural network is a trial-error process through multiple iterations. The neural network was configured in the training period and the configuration that gives the least training error has been selected for the testing phase. The detailed characteristics of the final neural network are given in Table 3.

Number of input	11
Number of output	11
Number of Hidden Layers	2
Error Function	*tLinear*
Training Algorithm	Incremental
Activation Functions	Elliot Symetric (1^{st} hidden layer)
	Sigmoid S Stepwise (2^{nd} hidden layer)
Number of epochs	1000
Training data set	First 14 days of the experiment duration
Testing data set	Data from the rest of experiment duration

Table 3: RNN Parameters for Behavior Profiling

In neural networks, there is no set way of defining the various network parameters. It was done by trial and error in the training phase. The objective was to minimize the training error. For both the subject 1 and subject 2, we ended up having similar neural network parameters as given in Table 3. For both subjects, once the ANN model has been built up, we fed the second group, i.e. the testing data set into the model. The average MSE of the testing data for the RNN came out to be just 6.21% for subject 1 and 3.52% for subject 2. The summary result for training and testing error for subject 1 and 2 is given in Table 4.

	Training Error	Testing Error
Subject 1	1.2%	6.21%
Subject 2	1.8%	3.52%

Table 4: RNN Mean Sq. Error for Behavioral Modeling

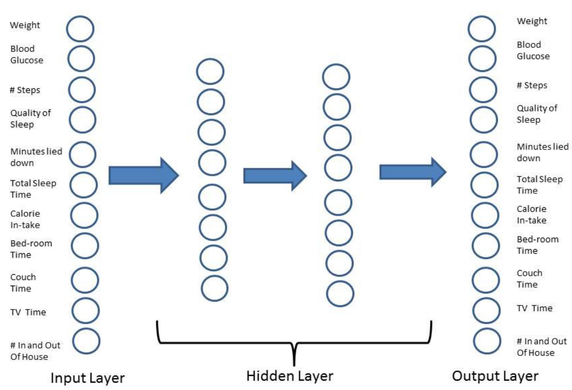

Figure 4: ANN Model for Behavior Profiling

The low testing error (Table 4) demonstrates that the RNN (Fig. 4) served the purpose of profiling the subject based on daily sensor data. Once the model has been built for a subject, the model can be used on daily basis to identify any major deviation from the profiled model for the subject and thus possible health condition of the subject that needs attention.

V. PREDICTING BLOOD GLUCOSE LEVEL

In this section, we demonstrate how the daily behavior data can be used to build an ANN based model for predicting blood glucose level. It is a known medical knowledge that calorie intake and the physical activity directly impact the blood glucose level [24]. However, based on various daily activities, it becomes difficult for a subject to know whether the daily activity and the calorie in-take have been appropriate to reach the target blood sugar level. In this section, we demonstrate an ANN based model that can be used by subject to predict the daily blood sugar level based on behavioral data captured by sensor. We propose two models for this purpose.

In both models, we use the behavioral data captured by sensors in day D to predict the blood glucose level in D+1 morning (Fig. 5). In the first model, we do not include the BG level of day D as input to predict the BG level of D+1. Whereas, in the second model, we include the BG level of day D as input of the model.

For this model, for subject 1 we have 20 data rows; note that we don't have the blood glucose (BG) level for 22nd day of the experiment. So we use the behavioral data for 20th day to predict the value for 21st day which is known. We prepare 20 rows, where the input is the behavioral and physiological data in day D and the output is the morning blood glucose level in day D+1. In similar fashion we also prepare the data rows for subject 2, where we will have 29 rows.

As before, we identified the first 14 days of data as training data set and the rest of the data set as testing data set. Thus we have 6 testing data rows for subject 1 and 15 testing data rows for subject 2. First we train a neural network model with the training data set and appropriately configure the neural network that provides the least error. The configuration of the neural network is given in Table 5.

Number of input	10
Number of output	1
Number of Hidden Layers	2
Error Function	*tanh*
Training Algorithm	Resilient
Activation Functions	Elliot Symetric (1st hidden layer)
	Sigmoid S Stepwise (2nd hidden layer)
Number of epochs	200
Training data set	First 14 days of the experiment duration
Testing data set	Data from the rest of experiment duration

Table 5: RNN Parameters for BG level Prediction

Next, we ran the testing data set through the model to measure the testing error. For subject 1, we got an error of 7.5% as follows,

$$\%\ Error = \frac{|\,\text{Predicted BG Level - Actual BG Level}\,| \times 100}{\text{Actual BG Level}}$$

$$\%\ Accuracy = 1 - \frac{|\,\text{Predicted BG Level - Actual BG Level}\,| \times 100}{\text{Actual BG Level}}$$

i.e. the model is able to predict the next day's blood glucose level with an average **accuracy of 92.5%** for subject 1. For subject 2, the error was 6.6%, i.e. the prediction accuracy for subject 2 was **93.4%.** The details of the testing and training errors are given in Table 6.

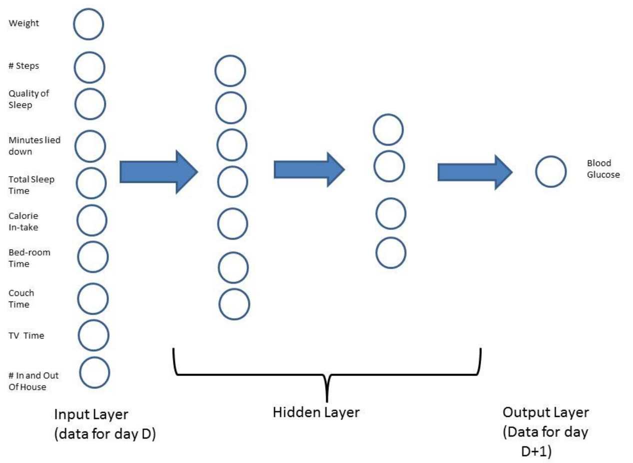

Figure 5: ANN Model Blood Glucose Level Prediction

	BG level of previous day not included in the model		BG level of previous day included in the model	
	Training Error	Testing Error	Training Error	Testing Error
Subject 1	3.3%	7.5%	3.1%	4.1%
Subject 2	2.4%	6.6%	2.9%	6.1%

Table 6: Training and Testing Error for Blood Glucose Modeling

Next, we added the blood sugar level of day D in the input layer. In this model, we predict the morning blood glucose level of day D+1 based on behavioral and physiological data in day D and the morning blood glucose level in day D. Other than addition of the day D morning blood glucose level in the input layer, the neural network structure and characteristics remains same as in Figure 5. Similar to the previous scenario, here also we divide our data into two sets training and testing. First we train the model and then we test it using the test data. We got a test error of only 4.1% for subject 1 and 6.1% for subject 2. The details of the training and testing error are given in Table 6.

The above results demonstrate two important aspects in our approach. First, if the blood glucose level of a day is known and is used to model and predict the blood glucose level for the next day, the accuracy will be higher, than if the blood glucose level is not at all available. The second, and the most important learning is, it is possible to model the blood glucose level (an important metrics for diabetic patients) based on daily behavioral data of a subject with an accuracy of about 93-94%.

To demonstrate the error visually, we plotted in Fig. 7 both the predicted and actual BG level for subject 2 when the previous day BG level has not been included in the model. We can definitely see from Figure 7, that our predicted values have followed the pattern of the actual values.

Additionally to demonstrate the dependency of BG level on our intervention, we did a regression analysis assuming BG level as the dependent variable, and calorie intake, physical activities (such as number of times in-out, steps walked, total idle time) and physiological data (such as weight) as dependent variable. We understand that with such a small data-set no statistical conclusion can be drawn. However, such a regression analysis will at least give some heuristic result. The regression result has been presented in Table 7. We can see that for subject 1, there is a high correlation of BG level to weight and idle time. For subject 2, there is a high correlation of BG level to number of steps and total number of in-out. Thus in both subjects the BG level is dependent on some variable related to physical activity, which is being influenced by persuasive technology.

II. CONCLUSIONS

We designed and build a in-home activity monitoring system using ambiant sensors and body-wearable sensors. Using a pre-post experiment method, the subject received daily text messages based on his/her behavior the previous day. These persuasive messages used strategies such as motivate, priase, guilt or reward to encourage positive behavior change. The subject also received a tailored health newsletter at the end of each week that summarized various physiological and biological parameters. The subject showed improvements in hbA1c levels. Although we were limited to only 2 subjects in our study, we consider these as case studies from which we can learn what works. Our aim in future is to scale this study up to several subjects to gain a deeper understanding of the potential impact of the technology. We further demonstrated that using ANN techniques it is possible to design predictive modeling software that can accurately predict BG values of diabetic patients. Such advance knowledge of the BG values can benefit the patient, can notify care givers to take action and can be crucial in saving lives.

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	Subject	Weight	Blood Glucose	Steps	Sleep Efficiency	Lying Time (Minutes)	Sleeping time (Minutes)	Calorie Intake	Bedroom Time not including sleeping (Minutes)	Total In-Out Number	Idle Time (minutes)
Max	1	202.60	155.00	12571.00	0.88	863.00	647.00	2277.00	1606.00	52.00	1912.00
	2	265.80	336.00	3942.00	0.92	644.00	565.00	2382.00	14.00	23.00	189.00
Min	1	191.40	108.00	2328.00	0.60	481.00	383.00	1120.00	27.00	0.00	216.00
	2	256.60	89.00	91.00	0.58	351.00	222.00	410.00	3.00	5.00	2.00
Mean	1	193.26	125.42	5251.42	0.78	660.47	509.74	1548.78	530.94	18.05	770.93
	2	261.70	190.41	2445.97	0.83	522.10	436.00	1514.58	6.52	10.33	71.83
STDEV	1	3.09	12.85	2644.60	0.07	100.22	74.87	291.65	384.16	14.93	430.92
	2	1.67	60.57	743.65	0.08	83.70	79.60	501.91	2.51	4.47	51.34

Table 2: Statistics for Collected Data

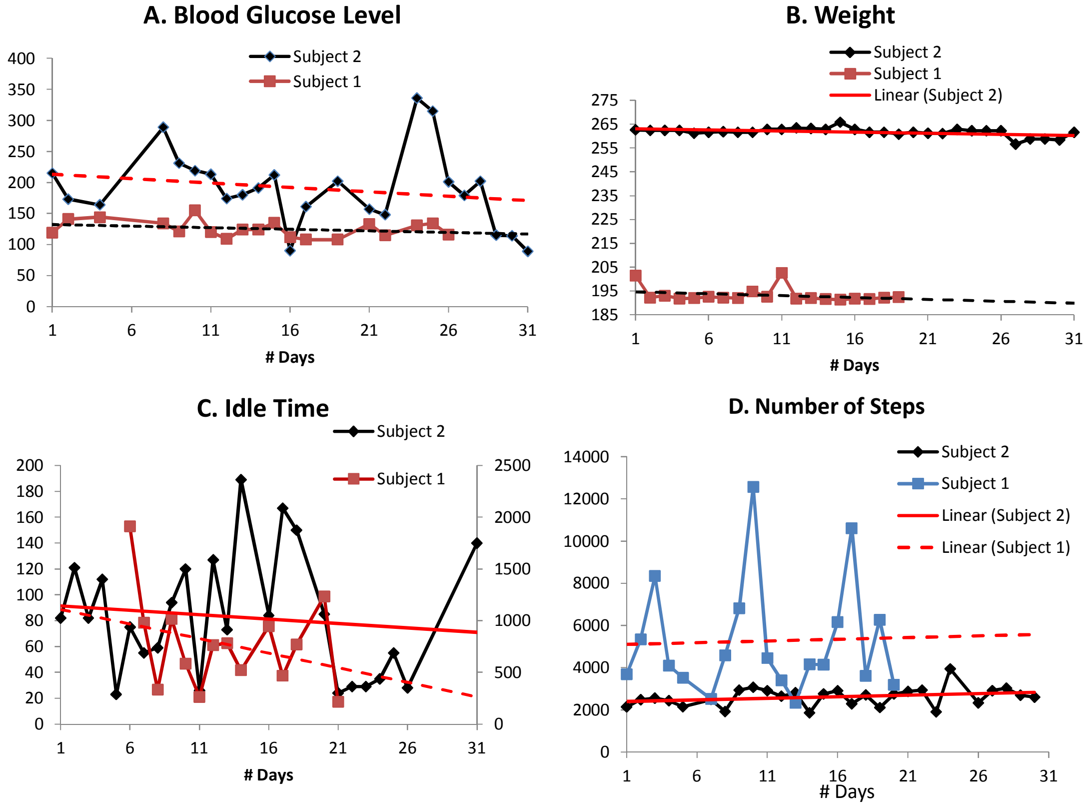

Figure 6: Physical and biological parameters results A) Blood glucose levels; B) Weight trends; C) Idle Time and D) Number of Steps Walked.

	Dependent Variables	p-Value	t-stat	Correlation Coefficient
Subject 1	Weight	0.0178	2.7847	0.8257
	Idle Time	0.0008	4.5413	
Subject 2	Steps	0.0095	2.8694	0.6471
	Total In-out number	0.0067	3.0239	

Table 7: Heuristic Dependency Analysis for BG

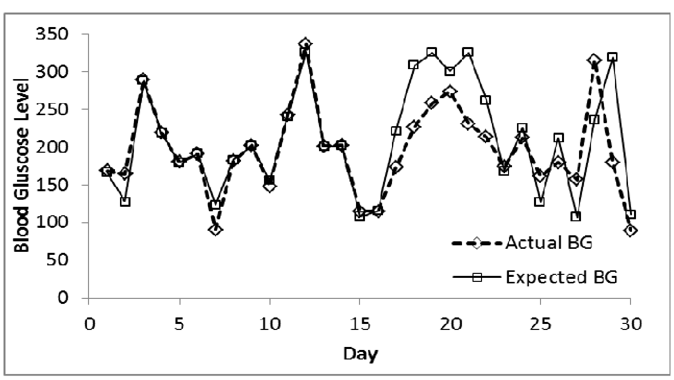

Figure 7: Comparison of Expected and Actual BG level for Subject 2