GLUCAGON: AI-Based Insulin Dosage Prediction Application

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Abstract:- *The automation of insulin treatment is the most challenging aspect of glucose management for type 1 diabetes owing to unexpected exogenous events (e.g., meal intake). In this article, we propose a reinforcement learning (RL) algorithm based on artificial intelligence (AI) for an application which predicts the optimized insulin dosage using the datasets obtained from CGM and activity band which continuously collects data from the victim. A bio-inspired RL designing method was developed for automated data integration. This strategy uses reward functions to represent the temporal homeostatic goal, as well as discount factors to represent an individual's unique pharmacological profile. The proposed strategy was tested in virtual patients from the FDA-approved UVA/Padova simulator with unscheduled meal intakes using a training method based on an RL algorithm. The trained policy demonstrated fully automated regulation in both the basal and postprandial phases for a single-meal experiment with pre-prandial fasting. The layer-by-layer relevance propagation gives interpret-able data on AI-driven decisions for sensor noise robustness, automatic postprandial management, and avoidance of insulin stacking. The accuracy of the application was also tested by comparing with conventional manner of blood glucose checking.*

Keywords: ***Diabetes Mellitus, Reinforcement Learning, Artificial Neural Networks***

1. INTRODUCTION

Medical science has been progressing under the shades of technological advancement and technical support. The capabilities of human being has been overridden by machines and programmed devices that ensures the right treatment for patients and accurate test and validation process that eradicates any risk. This progression is a big leap in comparison with old ways of treatment and care. Despite of any unhealthy life style and biogenic diseases, people now a days suffer from hereditary syndromes. Type 1 diabetes (T1D) is the most common condition which is considerably in above average levels of diagnosis. It is also called Diabetes mellitus or Juvenile diabetes as it is commonly diagnosed in children below age 13. It is an irreversible condition where the immune cells of the victim's body accidentally attacks the beta cells of the pancreas and completely destroys its ability to produce necessary insulin and thus shuts down the endocrine system. Any physical body needs energy for existence and it can only be gained when insulin converts the glucose and starch in blood into energy and store it in the cells to be utilized. In case of T1D patient, the victim suffers from terrible fatigue and nausea. Numerous technological advancements has been introduced to overcome and reverse this condition but it's been only managed to control and regulate the blood glucose level manually and doesn't has any progression in rejuvenating the pancreas system other than surgeries. This paper, introduces an ideology of mimicking the beta cells of pancreas so as it could successfully and accurately generate insulin dosages by understanding the victim's physical environment by collecting necessary data instantly.

It has been reported that around 70% of people around the world has been using conventional prescribed insulin dosages that may invite short term or long term consequences and risks the physical condition of the victim. This is happening because of miscalculated insulin dosages that doesn't relate to the person's homeostasis at all. A study conducted by University of Texas regarding diabetes mellitus found that numerous critical conditions and consequences such as kidney failure, lung disease, brain cells degradation, muscle degradation, diabetic retinopathy, cataract etc. has been affecting people with T1D even if they are on prescribed medical routine. This issue is the main concern that is being concentrated in this paper.

2. EXISTING SYSTEM

2.1 Review of Existing System

A conventional manner of injecting pre-set insulin dosage for a T1D patient is considered a risky and inconvenient strategy. It may result in over dosage of insulin which may be a reason for the hypoglycemic state where a person could experience short-term dizziness or traumatic condition, whereas under dosage of insulin may result in hyperglycemia state where a person could suffer from internal organ failure or cardiac arrest in long term. Frequent insulin shots are also considered inconvenient on ab daily basis. ' Insulin Pump Therapy ', solves these conventional inconveniences of frequent insulin shots as it permanently keeps a connected device over a T1D patient's abdomen which secretes insulin timing according to user interest. It consist of hardware components such as insulin chamber, secretion tube for insulin transmission, as well as a micro needle to inject into the victim’s body. This particular method known as Continuous subcutaneous insulin infusion (CSII) was introduced in early 70’s for the treating type 1 diabetes. It drastically manages to eradicate the inconveniences faced by victims of T1D by providing pre-set insulin dosages at specific intervals with the data collected from CGM.

CSII can had become a revolutionary invention across the world as it manages to solve frequent injections in toddlers and babies as it mainly affects children below 12 years of age. Study conducted by university of California confirms the stat obtained by Endocrine and Diabetic oriented surveys that 60% of the patients despite of their age suffers long term or short term complications from unregulated insulin dosage.

2.2 Disadvantages of Existing System

Insulin Pump Therapy was a revolutionary step to successfully manage T1D conditions and take a leap toward a technology that mimics biological pancreatic beta-cells. But, insulin preset condition is a major challenge to overcome to prevent hypoglycemic and Hyperglycemic conditions. IPT device manages to solve only the necessary problem of eradicating the inconvenience of frequent shots daily. The necessary health securities and blood glucose regulation cannot be ensured through pre-set insulin secretion. The human body manages to change its homeostasis according to certain external factors such as physical activity, calorie intake, and instantaneous blood glucose reading. Insulin dosage per instance has to be regulated according to these external conditions rather than preset values. In order to successfully optimize the overall insulin dosage, the IPT fails in managing to ensure reliability and consistency in certain situations.

3. PROBLEM DEFINITION

Type 1 Diabetes is a metabolic syndrome where the beta-cells of the pancreas fail to produce the necessary amount of insulin to convert glucose to needed energy. T1D is a permanent condition where no other treatment can be implemented other than synthetic insulin injection. Daily, insulin injection creates a considerable inconvenience to the patient as of traveling, calorie intake, moderate statutory factors etc.

In type 1 diabetes mellitus patients, tight glycemic control is linked to a higher risk of hypoglycemia. Diabetic individuals are obliged to change their lifestyle to adapt to and survive the disease. The most effective strategy to manage diabetes is to create a therapy that can adapt to the patient's needs.

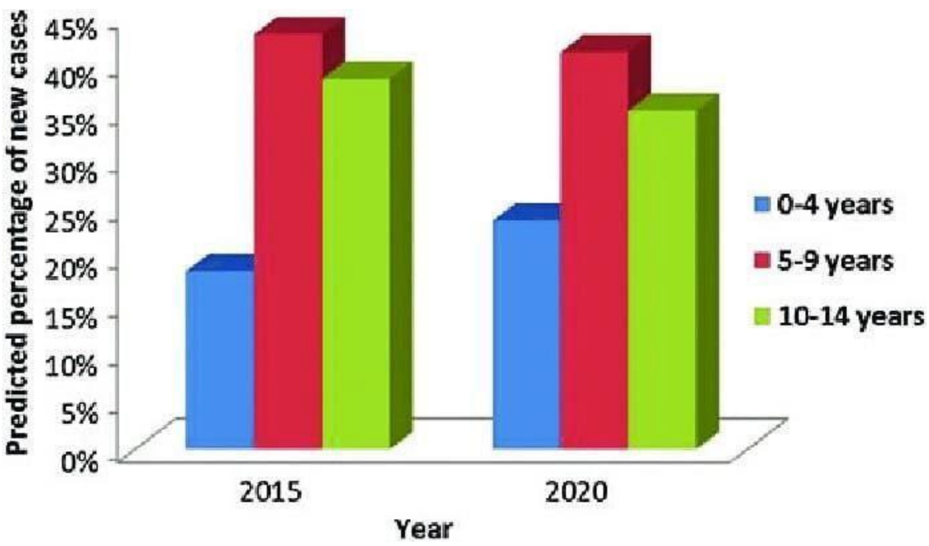


Fig-1 Type 1 diabetes diagnosis information based on age

4. METRICS

4.1 Reinforced Learning

It is the science of the decision-making process to obtain optimal behavior in an environment to maximize reward. It is an area of machine learning which defines how intelligent agents take actions in an environment to obtain rewards cumulatively. Here it uses the same fundamentals of a prediction algorithm that requires lesser historical data, working in an agent-based system to predict higher returns based on the current environment. This particular method assigns positive values to expected actions to encourage the agent and negative values to undesired behavior. It will be an execution in an iterative fashion based on rewards until the desired outcome is obtained.

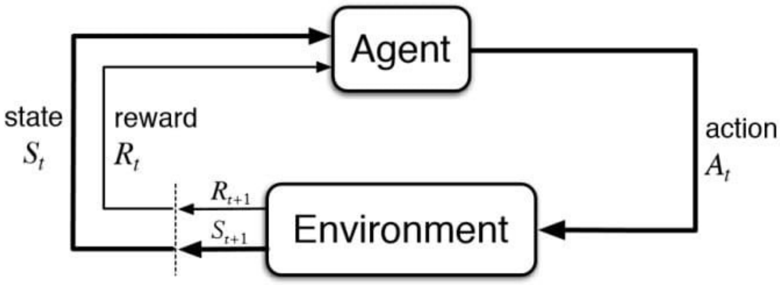


Fig-2 Reinforced Learning

4.2 Markov Decision Process

It is a process that provides a mathematical framework for modeling discrete time stochastic decision-making applications in particular situations where results are partially random or as expected. It is a sequential decision-making process where actions from a state influence the subsequent states other than immediate reward. Here, the Markov decision process is used to implement the glucose regulation problem. In the context of the glucose regulation problem, a metabolic system that depends on glucose regulation is said to be a Markov decision process environment which is represented using the tuple (S, A, T, R, y).

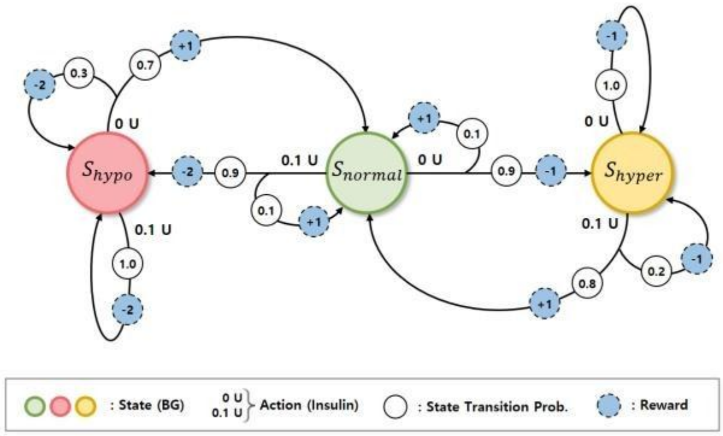


Fig-3 Markov Decision Process

In this system, S represents the set of states which are the glycemic conditions of a particular person, A represents the set of actions which are the possible insulin dosage, and T represents the state transition probabilities based on a particular person's metabolic responsiveness. The prediction process is based on the reward function which is represented by R: S x A, which gives the degree of blood glucose regulation. y is said to be the discount rate and it implies temporal optimization.

5. ANALYSIS

5.1 Data Exploration

The following data set consists of instantaneous blood glucose readings obtained from the Continuous Glucose Monitoring Device (CGM) at uniform intervals (1 hour). The data has been collected from type 1 diabetic persons with nominal values of cumulative insulin and the product of each variation in that particular nominal range which gives the insulin sensitivity which terms below. Specifically, the data set focus on a single person as this particular application considers the behavior and basic homeostasis of a person. The algorithm takes approximately 2-3 days of continuous data interpretation to adapt to the person's physical behavior. The preliminary set of data consists of readings obtained in 4 months of continuous glucose monitoring. The output of the CGM device is obtained in a graphical representation and it has been converted into numerical values calibrated to 24 readings per day in specific intervals.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	Dates	12:00 AM	1:00 AM	2:00 AM	3:00 AM	4:00 AM	5:00 AM	6:00 AM	7:00 AM	8:00 AM	9:00 AM	10:00 AM	11:00 AM	12:00 PM	1:00 PM	2:00 PM	3:00 PM	4:00 PM	5:00 PM	6:00 PM
2	01-01-2022	133	128	100	66	120	189	210	217	222	200	214	282	300	276	289	310	299	278	243
3	02-01-2022	129	125	120	75	94	128	148	151	156	145	183	238	256	244	234	256	249	210	182
4	03-01-2022	132	130	122	76	93	135	167	172	176	163	203	215	227	220	214	222	201	185	167
5	04-01-2022	106	100	98	88	110	122	138	127	124	124	162	237	278	262	265	278	156	147	126
6	05-01-2022	151	146	132	98	114	159	188	190	197	166	204	289	305	298	287	301	278	257	226
7	06-01-2022	108	98	67	56	76	80	89	95	98	101	103	146	199	190	187	210	175	154	117
8	07-01-2022	125	120	99	76	79	124	144	151	154	150	162	171	175	161	164	178	145	120	115
9	08-01-2022	115	110	102	87	111	120	132	142	143	145	204	219	235	224	218	229	192	183	166
10	09-01-2022	131	127	109	98	116	195	249	154	265	210	189	176	156	143	131	146	134	110	106
11	10-01-2022	137	126	113	67	146	195	211	218	220	185	218	247	275	243	212	244	201	184	176
12	11-01-2022	118	113	103	66	112	164	176	181	184	143	163	238	276	258	248	265	245	220	199
13	12-01-2022	135	128	124	87	119	147	166	175	190	148	173	239	287	276	266	277	256	226	196
14	13-01-2022	117	112	105	56	99	156	178	160	165	145	153	171	189	176	160	179	135	126	118
15	14-01-2022	105	100	88	77	98	153	163	171	176	142	147	155	159	155	147	165	123	101	85
16	15-01-2022	101	94	78	73	94	171	189	190	190	154	168	173	186	178	142	156	127	138	121
17	16-01-2022	106	97	64	62	86	122	148	152	156	140	143	153	156	144	131	143	128	125	114
18	17-01-2022	136	131	129	82	99	159	195	199	200	176	201	273	293	271	259	267	234	195	168
19	18-01-2022	185	178	164	146	138	124	113	119	122	128	217	284	310	305	294	333	296	273	226
20	19-01-2022	134	129	120	76	88	97	100	112	114	126	179	203	287	265	249	267	243	223	195
21	20-01-2022	127	122	111	71	84	136	167	171	173	152	161	183	147	141	131	135	101	125	111
22	21-01-2022	129	126	112	70	91	96	98	105	112	129	136	167	193	188	183	198	164	146	127
23	22-01-2022	137	127	111	90	117	110	106	106	108	123	126	130	137	130	128	134	110	142	124
24	23-01-2022	138	132	120	87	100	176	209	215	223	178	156	134	126	116	109	111	126	135	123
25	24-01-2022	142	137	127	80	102	127	135	143	149	143	156	177	186	164	147	154	152	127	113

Fig- 4 Representation of data-set

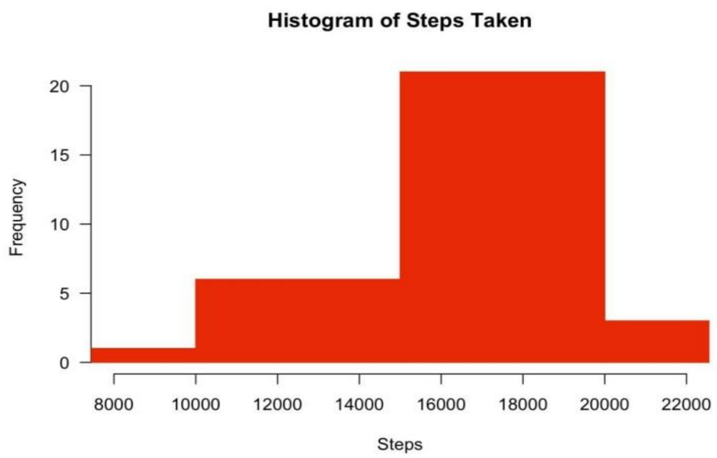
The 3 defined classes:

1) Hypoglycemia (values below 70, represented in yellow).

2) Normal (values range from 70 to 150, represented in green).

3) Hyperglycemia (values above 150, represented in red).

5.2 Data Visualization



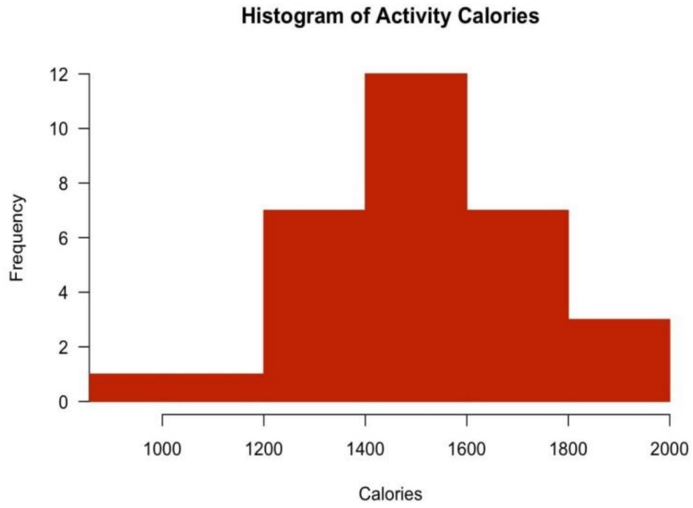


Fig- 5 Data set from activity tracker

Figure 5 represents the data sets from the activity band. Calorie updates from the device are obtained in a graphical representation and are converted to numerical format lately. This particular stage of data processing is required to calibrate the device to adapt to the person's physical condition and activity to which the overall blood glucose rate is related to the algorithm analyzes the numerical values and interprets each class according to the values obtained from the CGM device

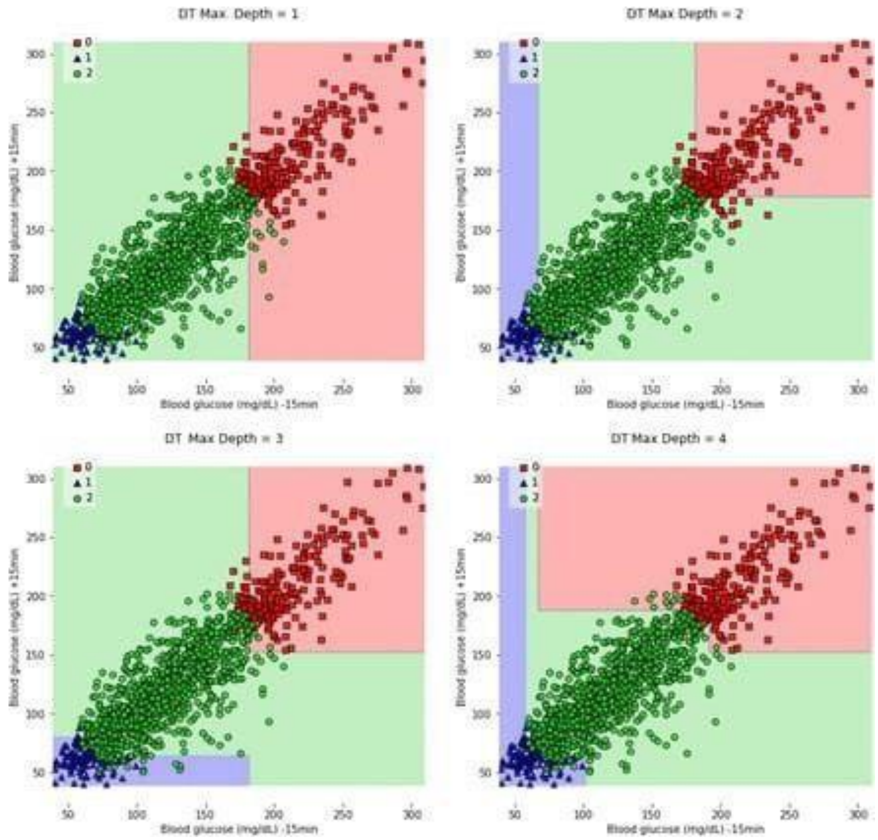


Fig- 6 Data set from CGM

Figure 6 represents the datasets obtained from the CGM device. The instantaneous blood glucose rate is obtained in a graphical representation. CGM device is capable of taking blood glucose readings every second or presenting uniform intervals according to the user's convenience. The data set from CGM is collected and elapsed to obtain every reading per hour format and thus obtaining 24 readings per day.

6. METHODOLOGY

6.1 Data Processing

Processing of data is carried out before the actual model is built and the training process was initiated using combined data sets from the hardware equipment which is mentioned in this paper. The steps carried out during the processing are:

- The obtained data sets from CGM and activity band were divided into training and validation sets.
- Executed classification algorithm to differentiate the three distinct classes.
- All three classes used during the training process were represented by three distinct colors.
- Each instance is normalized and a prediction algorithm is applied to each.
- To ensure the reliability of the predicted values, it has to perform backtracking to access prerecords.

7. IMPLEMENTATION

This system is supposed to solve the existing limitations of Insulin Pump Therapy as it works upon instantaneous data obtained via sensory devices and provides a well calculated and accurate Insulin dosage according to that data. This drastically reduces the risk of over-dosage and under-dosage thus further reduces problems which lead to hypoglycemia and hyperglycemia in short term. HBA1C graph is considered to be an effective way to determine the overall blood glucose regulation throughout a specific duration. The spikes and dips in the HBA1C, if significant, may result in concealing the real control state of this particular condition. This is why instantaneous readings of data and interpretation are required more often.

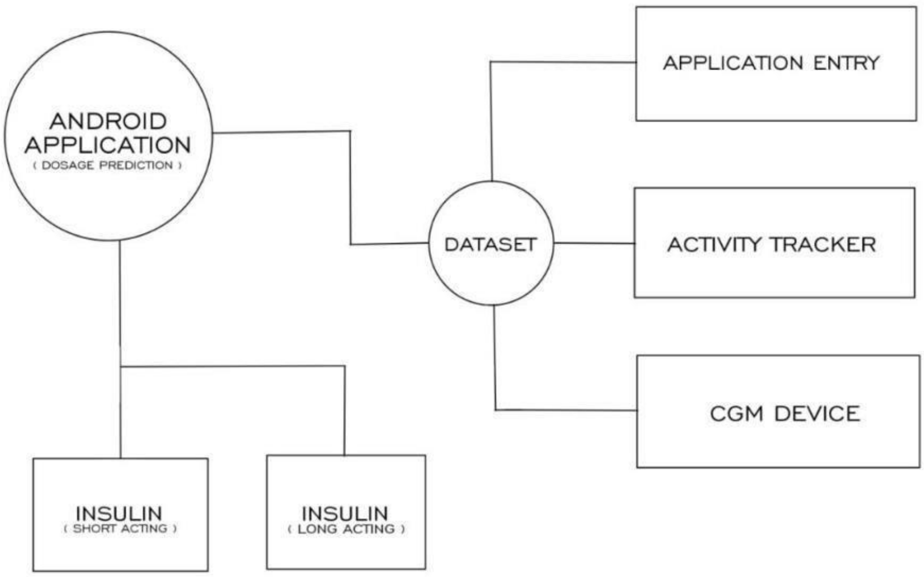


Fig- 7 Application implementation using an obtained data set

The Insulin prediction application is a clear case example of mimicking the beta-cells of the pancreas which helps in converting blood glucose into energy required for day-to-day activities. Under an uncontrolled blood glucose scenario, the victim may feel intense fatigue and dizziness. Mentioning the beta-cell working principle, an active human organ works continuously with the instantaneous interpretation of the current state of basic homeostasis of the body, thus creating efficient results. In this scenario, the same case is considered to be implemented to generate accurate results regarding the data generated.

The proposed system consists of a CGM (Continuous Glucose Monitoring) device, an Activity Tracker (Smart band), and a conventional application entry to track calorie intake and mealtime schedule. These are the datasets provided for the application of effective dosage prediction. The functionality is implemented in three phases:

PHASE I: DATASET COLLECTION

Continuous Glucose Monitoring (CGM) device collects the instantaneous blood glucose reading at any given time or uniform intervals. It also notifies the reading if any sudden spikes or dips in the glucose levels are identified and the algorithm will try to find the cause of this situation using the other provided datasets that influences the overall blood glucose levels. An activity tracker (Smart band) keeps tracking the overall physical activity of the victim throughout the day. Physical activity and related calorie variation are crucial in interpreting how much insulin is required for this particular individual at this particular moment. Insulin is scheduled to provide at the right time.

The calorie intake is given by the user directly into the application manually. This is basically for two things. At first, data regarding the actual calorie intake will help to calculate how much the glucose level will be supposed to spike after the meal and thus how much insulin is required despite other factors. Second, the time of meal intake by the user for identifying an approximate mealtime schedule for perfectly tracking an incoming glucose spike and being alert to optimize it.

PHASE II: INTEGRATING DATASET

The data set collected via PHASE I is completely independent. But, to predict the most accurate Insulin level, these datasets have to be co-related and co-interrelated. Insulin dosage prediction cannot be implemented from the data set obtained from CGM alone as the physical activity of the victim and the calorie intake also influence the overall blood glucose level. So, an optimal interpretation for these factors has to be obtained. This is done by incorporating reward functions in Reinforced learning design. The scenario where glucose is supposed to dip such as intense physical activity is given a positive reward when compared to the blood glucose reading at the instance and the scenario where glucose is supposed to spike such as excess calorie intake is given a 15negative reward compared to blood glucose at an instance. The comparison with the blood glucose reading at an instance is carried out because the reward system must be active until the blood glucose reading reaches the nominal range. Insulin must be provided whenever a negative reward is prior and the dosage depends upon the value of the negative reward. The higher the negative reward higher the insulin dosage. Whenever a positive reward is prior, the victim is supposed to have glucose intake or most probably go through mealtime. The body requires glucose and no insulin action is carried out in this instance.

PHASE III: INSULIN VARIANT SELECTION

Predicting the perfect amount of insulin alone can't solve the problem unless the type of insulin which is provided to the person is chosen right. The victim has to deal with the condition where the insulin must sustain its effect or not. There are conditions where the insulin effect must be active for a prolonged period such as nighttime or work time despite instantaneous actions. So, the algorithm has to choose between short-term insulin or long-term insulin according to a given condition. This decision is made from continuous tracking of the individual's mealtime schedule, inactivity schedule, and DNE (Do Not Engage) mode. To sustain blood glucose control over a prolonged period, long-acting insulin is provided. If DNE mode is active, the algorithm will monitor the current state of data and provide the necessary long-term insulin variant at once for keeping glucose level under control as it can't influence it anymore unless the user manages to deactivate DNE. In all other instances, the algorithm chooses short-term insulin for instant action. Short-term insulin is a bit challenging during nighttime conditions as if the physical state of completely inactive,this may lead to an instant dip in blood glucose reading more than it is supposed to be. So long-acting insulin is provided at night before the user's sleeping schedule.

By interpreting these three phases, the system can predict optimal insulin dosage for a person at a given instance. The obtained output can be integrated into existing Insulin Pump Therapy or it can be generated on the Android application for user convenience. If it is integrated into the IPT, it user doesn't have to deal with the inconvenience of frequently monitoring the situation, as it will be monitored by the algorithm with the given data set.

8. Results

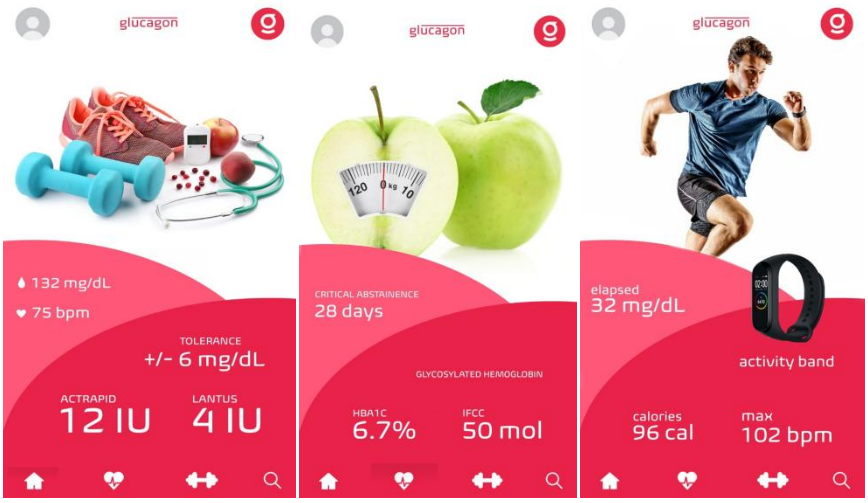


Fig- 8 Final output on an android application

Figure 8 shows the outlook of the application which has been developed based on the mentioned terms. The first interface refers to the dosage prediction section where the insulin dosage of multiple variants, insulin tolerance, blood glucose rate at the instance as well as the heart rate. The second interface refers to the HBA1C and FACC of the particular person based on the obtained data set as well as the overall elapsed period where the person is free from any hikes or dips from the normalized blood glucose level. The third interface refers to the activity tracking process based on the data set from the smart band. It denotes the overall calorie update, maximum endurance, and elapsed rate.

Minor glitches might be an issue that has been faced during the testing process. The reason for any miscalculated insulin prediction will be:

- Hardware failure and poor device calibration.
- Undefined application entry.
- Inconsistent usage of CGM.
- Overlapping of data.

9. CONCLUSION

This work has been developed by using Machine Learning tools to analyse and understand the overall physical environment of the user and hence predict the optimal insulin dosage at a particular instance. From the execution phase, the algorithm was able to interpret the given datasets from CGM as well as activity band give the right results. The future reference to this application will have profile to track datas of multiple person under the same device. The libraries used in this work is mostly mathematical and numeric value related and datasets was manually collected from victims of type 1 diabetes. Data set contains the set of blood glucose readings from 3 months of continuous monitoring. This work perhaps be the answer to miscalculated insulin dosage and consequences.

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