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Machine Learning Based Continuous Glucose Monitoring System

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Abstract

One of the most encouraging advancements to track blood sugar levels in people with diabetes who require insulin treatment is aclosed-loop insulin delivery system (also known as the artificial pancreas). Such a system incorporates continuous glucose monitoring (CGM), insulin (with or without glucagon) infusion, and a control algorithm to constantly direct blood glucose levels. In this model we incorporated machine learning based models to anticipate and forecast future glucose levels in the blood based on two study populations (CGM based and CGM- and accelerometery-based glucose predictions. We used data from The Maastricht Study, an observational, imminent, populace-based accomplice study. The Maastricht Study is broad phenotyping study that focuses on the etiology of type 2 diabetes (T2DM), its classic complications, and its arising co morbidities.

Models trained with CGM data were capable to accurately anticipate glucose values at 15 (RMSE: 0.19mmol/L; rho: 0.96) and 60 minutes (RMSE: 0.59mmol/L, rho: 0.72). Model performance was comparable in individuals with type 2 diabetes. Incorporation of accelerometer data only slightly improved prediction. Prediction models translated well to individuals with type 1 diabetes, which is reflected by high precision (RMSEs for 15 and 60 minutes of 0.43 and 1.73 mmol/L, respectively) and clinical safety. Hence machine learning models are able to predict the future glucose levels accurately and precisely than the traditional non-invasive methods like closed loop monitoring.

Keywords: Continuous Glucose monitoring, Machine Learning, Type1, Type 2 Diabetics prediction, Accelerometery.

Introduction

Diabetes is one of the present most prominent worldwide issues, and it is just increasing. Consistent estimating of blood glucose level is an essential for observing glucose blood level and setting up diabetes treatment strategies.[2]The expanding pervasiveness of diabetes involves an increase in incapacitating complications, like cardiovascular diseases. Keeping

up with plasma glucose levels inside the reference range is fundamental for the anticipation of diabetes-related confusions. One of the most encouraging advancementsto track blood sugar levels in people with diabetes who require insulin treatment is aclosed-loop insulin delivery system (also known as the artificial pancreas). Such a system incorporates continuous glucose monitoring (CGM), insulin (with or without glucagon) infusion, and a control algorithm to constantly direct blood glucose levels. Continuous glucose monitoring is wearable technology that makes it simpler to follow glucose levels over the long run. [22-23][11-12]

CGM is an instrument for individuals with diabetes. The sensor estimates glucose levels in the liquid under the skin, most CGM devices take readings every five minutes, all day and night.[3-4] The sensor needs to be changed consistently dependent on the device. Depending on the CGM system, glucose data from the sensor is sent to either a handheld device called a receiver (such as a cell phone), an app on your smart phone or an insulin pump. Using a CGM device can make it easier to manage Type 1 or Type 2 diabetes. Although this CGM uses non-invasive methods to monitor glucose level there are yet various issues that should be addressed in order to improve the individual components of closed-loop systems.[5] Sensors delay and sensor glitches (i.e., periods during which no glucose values are recorded) are the issues with CGM that are needed to overcome. Continuous glucose prediction is a possibly a suitable procedure to both handle sensor delay and bridge periods of sensor malfunction. [6] Glucose values can be precisely predicted using machine learning. In addition to this, including physical activity, which is considered to be a key factor for glucose control in daily life, could further improve glucose prediction. [7]

In this model, to what extent glucose values can be precisely anticipated at time spans of 15 and 60 minutes by a machine learning model that has been trained with a sliding timescale of glucose values preceding the forecasted values at a fixed interval has been studied. Also, we concentrated on whether glucose prediction can be further enhanced by including accelerometer-measured physical activity, and to what extent the results vary in a subgroup analysis of people with type 2 diabetes only.[8] For this, we used a large population of individuals with either normal glucose metabolism (NGM), prediabetes, or type 2 diabetes who at a time underwent CGM and continuous accelerometry during one-week duration. Lastly, the freely accessible OhioT1DM Dataset is used to investigate whether CGM-based forecast models would mean people with type 1 diabetes, the essential objective populace for closed-loop insulin delivery [9].

Literature Survey

Closed-loop insulin delivery systems, which integrate continuous glucose monitoring (CGM) and algorithms that continuously guide insulin dosing, have been shown to improve glycaemic control. We used data from The Maastricht Study, an observational population-based cohort that comprises individuals with normal glucose metabolism, prediabetes, or type 2 diabetes [1]. In recent years, with the rise of global diabetes, a growing number of subjects are suffering from pain and infections caused by the invasive nature of mainstream commercial glucose meters. Non-invasive blood glucose monitoring technology has become

an international research topic and a new method which could bring relief to a vast number of patients [10].

Machine Learning Based Model

For this model, we used data from The Maastricht Study, an observational, imminent, populace-based accomplice study. The Maastricht Study is broad phenotyping study that focuses on the etiology of type 2 diabetes (T2DM), its classic complications, and its arising co morbidities. People aged between 40 and 75 years and living in the southern part of the Netherlands were qualified for participation**.** Participants were selected through mass media campaigns and from the municipal records and the regional Diabetes Patient Registry by means of mailings. For reasons of productivity, enrolment was separated by known kind 2 diabetes status, with an oversampling of people with type 2 diabetes. In general, the assessments of every member were performed within a time span of three months [14]. From 19 September 2016 until 13 September 2018, members were invited to also undergo CGM. During this period, a chose group of as of late included members were encouraged to return for CGM. It is observed that in these people only, there was a median time interval of 2.1 years between CGM and all other measurements [13]. The current report incorporates cross-sectional information of the 851 members who had basically 48h of CGM information accessible and were grouped with NGM, prediabetes, or type 2 diabetes [15].

Continuous Glucose Monitoring

As defined previously, CGM is an instrument for individuals with diabetes. The sensor estimates glucose levels in the liquid under the skin, most CGM devices take readings every five minutes, all day and night In this model, members were requested to perform self-estimations from blood glucose four time every day.[17] Diabetes drug use was permitted, and no dietary guidelines were given. We just included people with at minimum 48h of CGM yet rejected the first 24h of CGM from examination as a result of inadequate calibration. For the glucose expectation investigations, all leftover glucose data points were utilized. We also calculated mean sensor glucose, standard deviation (SD), and coefficient of variation (CV) with the use of Glycemic Variability Research Tool software [16].

Accelerometery

Accelerometry is utilized to gauge human motion. These devices record patterns of movements. Accelerometry-based activity monitors are typically small battery-operated devices worn on a belt or waistline, or on the wrist. They measure acceleration in three planes: anterior-posterior; vertical; and medial-lateral. In this model triaxial activPAL3 accelerometer is used. No physical activity instructions were given.PAL Software Suite version 8 was used to convert the event-based accelerometry data records into 15-second interval data files. We used the composite of X, Y, and Z accelerations for each 15-second interval as the measure of physical activity [18].

Evaluation of participant attributes

Classification of glucose metabolism status (GMS) either as NGM, prediabetes, or type 2 diabetes depending upon both a standardized 2-hour 75 gram oral glucose tolerance test and use of glucose-lowering medication has been done. In addition to this, smoking status and history of diabetes dependent on surveys, estimated weight and height-to calculate body mass index (BMI)-and office blood pressure during a physical assessment and estimated HbA1c including lipid profile in fasting venous blood is determined.[19]

Dataset Development

An outline of data pre-processing, model development and model assessment is interpreted in Fig 1 [1]. To prepare models in anticipating future glucose values, two separate datasets were built. The first dataset comprised of only the members' six-day, five-minute interval CGM data (n = 851) and the second dataset comprised of both CGM and accelerometry information (n = 540).

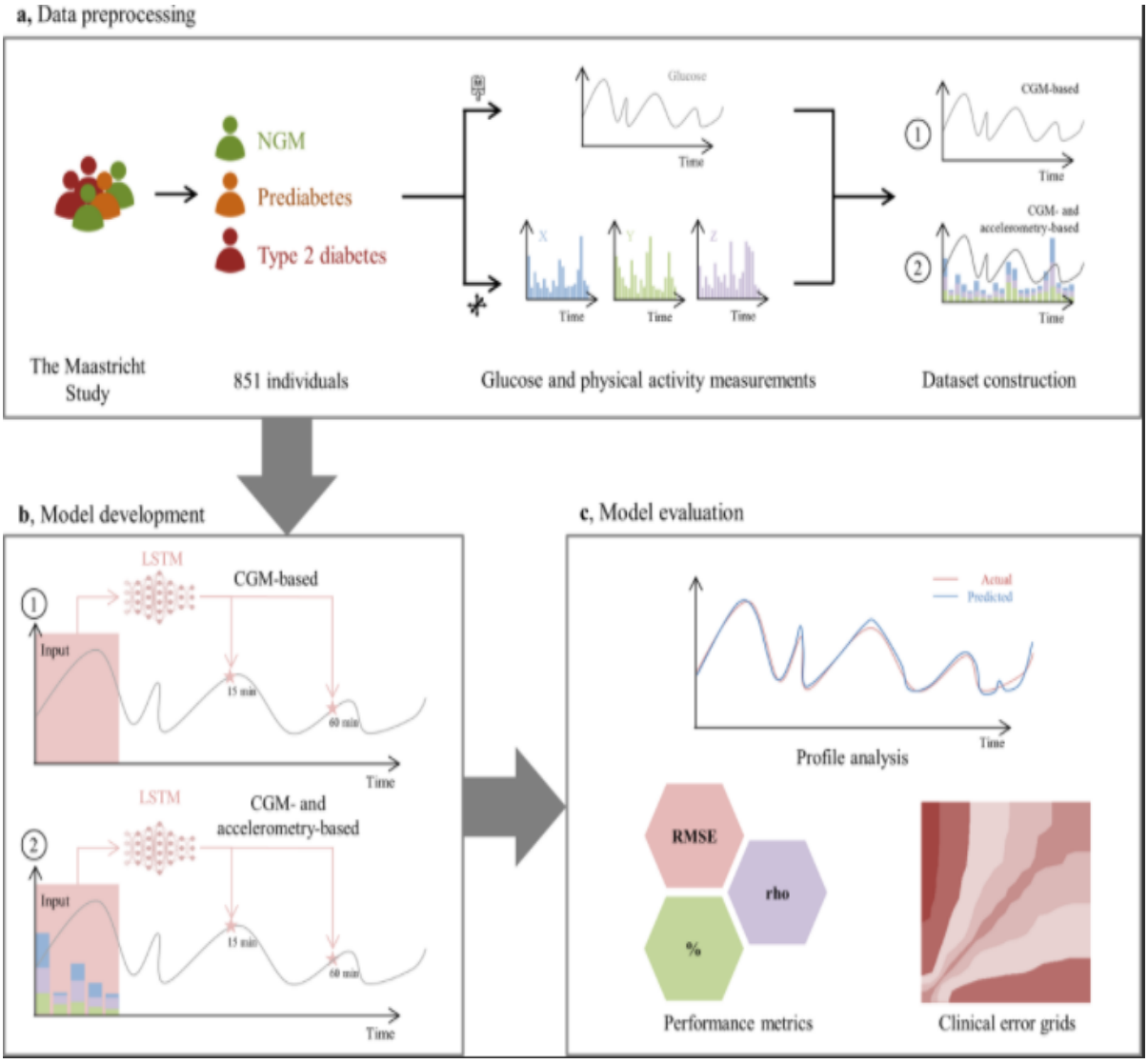

Figure 1.An overview of data pre-processing, model development and model assessment

To match CGM data which is determined at 5-minute intervals and accelerometry data which is determined at 15-second intervals in the second dataset, we linearly interpolated glucose values between two glucose data points with a frequency of 15 seconds. Steady and aligned frequency intervals across these attributes are a statistical precondition for this type of model development. [20] the study populaces were arbitrarily parted into a training (70%), tuning (10%), and assessment (20%) dataset such that data from a given individual is available just in one set. The training set was utilized to train the proposed models, The tuning set was used to iteratively improve the models by choosing the best model designs and hyper parameters. At last, the best models were assessed on the independent evaluation set that was retained during model development.

This model operates consecutively over CGM and accelerometry data (Fig 1, b) [22]. At every individual time point, 30 minutes of earlier time series information were given to the statistical model, in view of which it anticipated glucose esteems at indicated time spans. For this study, we set these time span at 15 and 60 minutes. In the current study, we assessed autoregressive integrated moving average, support vector regression, gradient-boosting systems, shallow and deep multi-layer perceptron neural networks, and several recurrent neural network (RNN) architectures, including classical RNN, gated recurrent units, long-short term memory (LSTM) networks, and all of its bi-directional variants.[21]

Training the Model

RNN architecture had prevalent performance at the 15-minute prediction interval while the LSTM network outperformed all other designs at the 60-minute prediction interval (Table 1, RMSE: 0.941 [0.937-0.945]). This architecture runs sequentially over time series data and can certainly display the recorded setting of an individual by changing an internal state through time. In particular, we planned this design to anticipate both time intervals simultaneously, frequently cited as “multi-task learning”, which aims to share information among prediction tasks.[23]

Then, we assessed a wide range of hyperparameter mixes for this network. This resulted in a multi-task LSTM architecture, comprising of three layers, along with a dropout layer with a total of 56-104 neurons. During training, exponential learning-rate decay through the Adam optimization scheme has been utilized. The best approval results were accomplished by utilization of an initial learning rate with a decay of 0.001 every 1,000 training steps, with a batch size of 1024, and a back-propagation through a time span of 30 minutes. During the training, the loss function used is the mean average of the mean-squared error function of all predictions. The most quantity of epochs was 50.000 with an early preventing criterion (primarily based totally on 20% hold-out data) set to 250 epochs. Python programming language with the packages NumPy, Pandas, keras, Scikit-learn and TensorFlow (version 2.0.1, beta) is used.

Table 1

Prediction window and baseline model		CGM-based glucose prediction		Combined glucose prediction	
		Rho	**RMSE, mmol/L**	**Rho**	**RMSE, mmol/L**
15 minutes	ARIMA	0.842 [0.837-0.848]	0.504 [0.490-0.518]	0.834 [0.829-0.840]	0.498 [0.492-0.505]
	SVR	0.791 [0.781-0.802]	0.558 [0.549-0.567]	0.703 [0.694-0.712]	0.612 [0.601-0.622]
	LightGBM	0.783 [0.767-0.795]	0.589 [0.577-0.601]	0.783 [0.771-0.794]	0.497 [0.582-0.613]
	Shallow MLP	0.810 [0.804-0.816]	0.517 [0.506-0.529]	0.763 [0.754-0.772]	0.592 [0.581-0.603]
	Deep MLP	0.807 [0.797-0.818]	0.511 [0.504-0.518]	0.828 [0.819-0.837]	0.510 [0.503-0.517]
	RNN	0.894 [0.887-0.902]	0.485 [0.481-0.490]	0.890 [0.882-0.898]	0.477 [0.472-0.482]
	LSTM	0.872 [0.865-0.879]	0.482 [0.477-0.487]	0.884 [0.878-0.890]	0.501 [0.496-0.506]
16 minutes	ARIMA	0.307 [0.284-0.329]	1.543 [1.489-1.623]	0.303 [0.283-0.322]	1.502 [1.455-1.568]
	SVR	0.388 [0.376-0.398]	1.386 [1.322-1.452]	0.394 [0.382-0.405]	1.412 [1.350-1.475]
	LightGBM	0.500 [0.491-0.508]	1.118 [1.098-1.136]	0.498 [0.485-0.511]	1.128 [1.107-1.148]
	Shallow MLP	0.503 [0.495-0.511]	1.081 [1.074-1.088]	0.483 [0.470-0.495]	1.081 [1.070-1.092]
	Deep MLP	0.496 [0.484-0.509]	1.108 [1.100-1.115]	0.515 [0.502-0.528]	1.108 [1.099-1.017]
	RNN	0.591 [0.581-0.600]	0.989 [0.983-0.995]	0.596 [0.589-0.603]	0.992 [0.984-0.998]
	LSTM	0.605 [0.593-0.616]	0.941 [0.937-0.945]	0.602 [0.595-0.609]	0.992 [0.919-0.926]

Interpretation of the predicted models to the OhioT1DM Dataset

We utilized information from the OhioT1DM Dataset to investigate whether our CGM-based expectation models would translate to people with type 1 diabetes. It is a freely available data set for scientific purposes and consists data of 6 people with type 1 diabetes who were all using insulin pump therapy and CGM.

The participants were given the interstitial glucose values every five minutes for an eight-week period. First, in order to also include 30-minute prediction, the primary CGM-based models on the main study population with identical hyper parameters and settings were

retrained. Further, evaluation of the main CGM-based model on the test portion of the OhioT1DM Dataset (20%) is made. Next, optimization of the main CGM-based model was done by training it on the train portion of the OhioT1DM Dataset. Specifically, this model was trained by using an Adam optimizer with a learning rate of 10−4, a batch size of 1024, a maximum of 10.000 epochs and an early stopping criterion depending upon 20% of the training data set, to 100 epochs. Further, this optimized model was evaluated on the test portion using performance metrics and safety error grids.

Model evaluation

Model evaluation was performed in the independent evaluation sets of individuals that were not used during model development (Fig 1, c).We employed many measurements to assess the performance of the models: root-mean-square error (RMSE), proportion of predicted values within 5% or 10% of actual glucose values, and Spearman's rank correlation coefficient (rho). Bootstrapping was performed to obtain 95% confidence intervals for each of these measurements**.** Lastly, we conducted several sensitivity analysis in our main study populace by stratifying model performance for GMS (i.e., separate results for NGM and prediabetes); day (06.00 to 24.00h) and night (24.00 to 06.00h); and low or high glucose variability, defined as the 97.5th percentile of CGM-assessed SD in individuals with NGM (SD > 1.37 mmol/L) .Typically distributed data is represented as mean ± SD, non-normally distributed data as median and interquartile range, and categorical data as n (%)

Results

Models trained with CGM data were capable to accurately anticipate glucose values at 15 (RMSE: 0.19mmol/L; rho: 0.96) and 60 minutes (RMSE: 0.59 mmol/L, rho: 0.72). Model performance was comparable in individuals with type 2 diabetes. Incorporation of accelerometer data only slightly improved prediction. Prediction models translated well to individuals with type 1 diabetes, which is reflected by high precision (RMSEs for 15 and 60 minutes of 0.43 and 1.73 mmol/L, respectively) and clinical safety

Table 2 describes the overall and type 2 diabetes-stratified characteristics of the CGM-based as well as CGM- and accelerometery-based glucose prediction study populations. The overall traits of participants were generally comparable with regard to BMI, glycaemic indices, lipid profile, sex, and blood pressure(bp), despite the fact that the latter contained fewer participants with prediabetes or type 2 diabetes. Further, the members with type 2 diabetes in the CGM- and accelerometry-based glucose prediction population were more often newly diagnosed with type 2 diabetes. These participants didn't used glucose-lowering medication frequently.

Table 2

	CGM-based glucose prediction		CGM-and accelemotry-based glucose prediction	
Characteristic	**Total (n=851)**	**T2D (N=197)**	**Total (n=540)**	**T2D (n=68)**
Age, years	59.9 ± 8.7	62.4 ±7.8	59.1 ±8.7	62.0 ± 6.9
Women,n(%)	418 (49.1)	69 (35.0)	276 (51.1)	22 (32.4)
BMI, Kg/m^2	27.2 ± 4.4	29.7 ± 4.7	26.5 ± 4.0	28.6 ± 4.1
Newly diagnosed T2D, n (%)	70 (8.2)	70 (35.5)	35 (6.5)	35 (51.5)
Glucose metabolism status				
NGM/PreD/T2D,n	470/184/197	-	372/99/68	-
NGM/PreD/T2D, %	55.2/21.6/23.1	-	69.1/18.3/12.6	-
Fasting plasma glucose, mmol/L	5.4 [5.0-6.2]	7.3 [6.5-8.4]	5.3 [4.9-5.8]	7.2 [6.3-8.4]
2-h post-load glucose, mmol/L	6.7	13.6	6.2	12.5
	[5.2-9.1]	[11.7-16.2]	[5.0-7.7]	[11.3-16.6]
HbA_{1c}%	5.7 ± 0.8	6.7 ±1.0	5.6 ± 0.6]	6.4 ± 0.9
HbA_{1c}, mmol/mol	39.1 ± 8.3	49.2 ± 10.8	37.3 ± 6.2	46.9 ± 10.2
Sensor glucose				
Mean, mmol/L	6.1 [5.7- 6.7]	7.5 [6.8-8.7]	5.9 [5.6-6.4]	7.3 [6.5-8.2]
SD, mmol/L	0.84	1.51	0.79	1.46
	[0.68-1.18]	[1.14-1.95]	[0.66-1.01]	[0.94-1.99]
SD > 1.37 mmol/L,n(%)	142 (16.7)	115 (58.4)	50 (9.3)	36 (52.9)
CV, %	14.0	19.3	13.3	19.2
	[11.6-17.6]	[15.9-24.0]	[11.2-16.8]	[14.5-24.1]
Diabetics medication use,n(%)	109 (12.8)	109 (55.6)	27 (4.8)	27 (39.7)
Insulin	19 (2.2)	19 (9.6)	4 (0.7)	4 (5.9)
Metformin	104 (12.2)	104 (53.1)	27 (5.0)	27 (39.7)
Sulfonylureas	21 (2.5)	21(10.7)	6 (1.1)	6 (8.8)
Thiazolidinediones	0 (0)	0 (0)	0 (0)	0 (0)
GLP-1 analogues	3 (0.4)	3 (1.5)	1 (0.2)	1 (1.5)
DDP-4 inhibitors	1 (0.1)	1 (0.5)	0 (0)	0 (0)
SGLT-2 inhibitors	1 (0.1)	1 (0.5)	0 (0)	0 (0)
Office SBP, mmHg	133.3 ± 18.0	139.4 ± 15.6	132.2 ± 17.9	137.7 ± 15.3
Office DBP,mmHg	75.2 ± 10.2	77.7 ± 10.5	74.7 ± 10.1	77.7 ± 9.6
Antihypertensive medication use, n(%)	305 (35.9)	126 (64.3)	162 (30.0)	41 (60.3)
Total-to-HDL cholesterol ratio	3.5 [2.8-4.3]	3.6 [2.9-4.3]	3.4 [2.8-4.3]	3.7[2.8-4.6]
Triglycerides, mmol/L	1.3 [0.9-1.8]	1.5 [1.0-2.1]	1.2 [0.9-1.7]	1.6 [1.0-2.3]

Lipid-modigying medication use,n(%)	212 (24.9)	115 (58.4)	100 (18.5)	39 (57.4)
Smoking status				
Never/former/current,n	327/415/106	67/104/26	214/253/70	19/36/13
Never/former/current,%	38.6/48.9/12.5	34.0/52.8/13.2	39.9/47.1/13.0	27.9/52.9/19.1

Future scope

The machine learning models have proven to be able to predict the glucose levels in the blood accurately. The future scope of this study

can be extended to Machine Leaning with the combination of IoT can give the real time results .The advancements of the Internet of items and their applications have made an extraordinary improvement by becoming these days more open and more accessible, permitting countless items to be interconnected through the Internet in a few fields that are the field of wellbeing, home robotization, modern assembling, and so on In the field of keen wellbeing, there are a few applications that plan to further develop the mind and work on the personal satisfaction of patients with constant sicknesses. Utilizing IoT, portable wellbeing administration turns out to be more significant as it assumes a vital part in checking and controlling patients who experience the ill effects of persistent sicknesses like cardiovascular illness and diabetes. Indeed, to realize an IoT application in this field, the one must have assured the recording of a large amount of data collected by using measurements of the medical signs on the patients. Machine learning (ML) is a powerful tool that delivers insights hidden in Internet of Things (IoT) data.ML enables the IoT to demystify hidden patterns in bulk data for ideal forecast and recommendation frameworks.

Conclusion

In this model, it is observed that Machine Learning models able to precisely and safely anticipate glucose values for up to 60 minutes in individuals with, NGM, prediabetes, or type 2 diabetes. Moreover, interpretation of the expectation models to people with type 1 diabetes showed empowering results. The prediction model can be used to further develop closed-loop insulin delivery systems by overcoming sensor delay and sensor malfunctions. Machine Leaning based models are able to precisely anticipate the real glucose profiles at 15 minutes, as reflected by some objective performance measurements**.** Thus, this is an ultimate method to accurately measure glucose level without invasive methods and other difficulties.

References

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0253125#pone.0253125.ref013.

Weisman A, Bai JW, Cardinez M, Kramer CK, Perkins BA. Effect of artificial pancreas systems on glycaemic control in patients with type 1 diabetes: a systematic review and meta-analysis of outpatient randomised controlled trials. Lancet Diabetes Endocrinol. 2017; 5(7): 501-12. Epub 2017/05/24. pmid: 28533136.

Liu Tang , Shwu Jen Chang , Ching-Jung Chen 3,and Jen-Tsai Liu 1,-Non-Invasive Blood Glucose Monitoring Technology: A Review.

Kumareswaran K, Thabit H, Leelarathna L, Caldwell K, Elleri D, Allen JM, et al. Feasibility of closed-loop insulin delivery in type 2 diabetes: a randomized controlled study. Diabetes Care. 2014; 37(5):1198-203. Epub 2013/09/13. pmid: 24026542.

Blauw H, Keith-Hynes P, Koops R, DeVries JH. A Review of Safety and Design Requirements of the Artificial Pancreas. Ann Biomed Eng. 2016; 44(11):3158-72. Epub 2016/11/04. pmid:27352278; PubMed Central PMCID: PMC5093196.

The Maastricht Study: an extensive phenotyping study on determinants of type 2 diabetes, its complications and its comorbidities Miranda T. Schram, Simone J. S. Sep, Carla J. van der Kallen, Pieter C. Dagnelie, Annemarie Koster, Nicolaas Schaper, Ronald M. A. Henry & Coen D. A. Stehouwer.

Foreman YD, Brouwers M, van der Kallen CJH, Pagen DME, van Greevenbroek MMJ, Henry RMA, et al. Glucose variability assessed with continuous glucose monitoring: reliability, reference values and correlations with established glycaemic indices-The Maastricht Study. Diabetes Technol Ther. 2019. Epub 2019/12/31. pmid:31886732.

VR Allugunti, CKK Reddy, NM Elango, PR Anisha-Intelligent Data Engineering and Analytics, 2021 *Prediction of Diabetes Using Internet of Things (IoT) and Decision Trees: SLDPS*.

VR Allugunti, NM Elango "Development of a Generic Secure Framework for Universal Device Interactions in IoT of Fifth Generation Networks".

Viswanatha Reddy Allugunti-Internet of Things Based Early Detection of Diabetes Using Machine Learning Algorithms: Dpa in International Journal of Innovative Technology and Exploring Engineering.

Viswanatha Reddy Allugunti, NM Elango-Diabetes Diagnosis and Prognosis Using Machine Learning Approaches: A Survey.

Kishor Kumar Reddy C Viswanatha Reddy Allugunti, Elango N M-Diabetes Kaggle Dataset Adequacy Scrutiny using Factor Exploration and Correlation.

Allugunti, V.R., Kishor Kumar Reddy, C., Elango, N.M., Anisha, P.R. (2021). Prediction of Diabetes Using Internet of Things (IoT) and Decision Trees: SLDPS. In: Satapathy, S., Zhang, YD., Bhateja, V., Majhi, R. (eds) Intelligent Data Engineering and Analytics. Advances in Intelligent Systems and Computing, vol 1177. Springer, Singapore. https://doi.org/10.1007/978-981-15-5679-1_43.

Dang, N., Khanna, A., Allugunti, V.R. (2021). TS-GAN with Policy Gradient for Text Summarization. In: Khanna, A., Gupta, D., Pólkowski, Z., Bhattacharyya, S., Castillo, O. (eds) Data Analytics and Management. Lecture Notes on Data Engineering and Communications Technologies, vol 54. Springer, Singapore. https://doi.org/10.1007/978-981-15-8335-3_64.

V. Reddy Allugunti and N. Elango, "Development of a Generic Secure Framework for Universal Device Interactions in IoT of Fifth Generation Networks," *2018 Second*

World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4), 2018, pp. 238-245, doi: 10.1109/WorldS4.2018.8611592.

Prof. D. Jayaramaiah, A.Prasanth, A.Viswanatha Reddy, Dr. Anirban Basu, 2012, Multi Agent Management System for Next Generation Mobile Networks. [MAMS for NGMN], International Journal of Engineering Research & Technology (IJERT) Volume 01, Issue 07 (September 2012)

Prof. D. Jayaramaiah, A. Viswanatha Reddy, Srikishan. D. Agent based User Interface Design for Mobile Cloud Computing Environment (AUID), International Journal of Engineering Innovations and Research(IJEIR) Volume 1 Issue 3, May 2012.

Prof. D. Jayaramaiah, A. Prasanth, A. Viswanatha Reddy, Dr. Anirban Basu, 2012, Multi Agent Management System for Next Generation Mobile Networks. [MAMS for NGMN], International Journal of Engineering Research & Technology (IJERT) Volume 01, Issue 07 (September 2012).

Reddy, V., Allugunti, M, E. & Reddy, C. K. (2019). Internet of things based early detection of diabetes using machine learning algorithms: Dpa. International Journal of Innovative Technology and Exploring Engineering, 8(10):1443-1447. doi: 10.35940/ijitee.A1013.0881019.

Basu, Anirban. “Agent Based QoS Provisioning for NGMN (LTE).” (2013).

V. Reddy Allugunti and N. Elango, "Development of a Generic Secure Framework for Universal Device Interactions in IoT of Fifth Generation Networks," *2018 Second World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4)*, 2018, pp. 238-245, doi: 10.1109/WorldS4.2018.8611592.