sciendo

ISSN 1335-8871

MEASUREMENT SCIENCE REVIEW

Journal homepage: https://content.sciendo.com

A Cloud-Connected Digital System for Type-1 Diabetes Prediction using Time Series LSTM Model

K.Priyadarshini[1*], Alanoud Al Mazroa[2], Mohammad Alamgeer[3], V. Subashree[4]

[1]*Department of Electronics and Communication Engineering, K.Ramakrishnan College of Engineering, Samayapuram, Trichy, India, kpriyaanilesh@gmail.com*
[2]*Department of Information Systems, College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University (PNU), P.O. Box 84428, Riyadh 11671, Saudi Arabia , aalmazroa@pnu.edu.sa*
[3]*Department of Information Systems, Applied College at Mahayil, King Khalid University, Saudi Arabia, mabdol@kku.edu.sa*
[4]*Department of ECE, Saveetha Engineering College, Chennai , India, subsshreevsh@gmail.com*

Abstract: Millions of people worldwide suffer from diabetes, a medical condition that is spreading at an accelerating pace. Numerous studies show that risk factors that may arise from diabetes can be avoided if the disease is detected early. The health-care monitoring system has benefited greatly from early diabetes prediction made possible by the integration of Deep Learning (DL) and Machine Learning (ML) algorithms. The objective of many early studies was to increase the prediction model accuracy. However, DL algorithms often cannot fully exploit the potential of the available datasets because they are too small. This study includes a very accurate DL model as well as a novel system that integrates cloud services and allows users to directly enhance an existing data set, which can increase the accuracy of DL techniques. Therefore, the Long Short-Term Memory (LSTM) model with controller is chosen for efficient type-1 diabetes prediction. Experimental validation of the proposed Nonlinear Model Predictive Control (NMPC)_LSTM algorithm method is compared with other conventional DL algorithms. The proposed controller method achieves excellent blood glucose set point tracking and the proposed algorithms achieves 98.95% accuracy for the obtained data. It outperforms other existing methods with an increase in percentage accuracy compared to the Benchmark Pima Indian Diabetes Datasets (PIDD).

Keywords: Cloud controller, diabetes, long short-term memory, glucose-insulin, non-linear predictor, time series.

1. INTRODUCTION

Diabetes, a chronic disease, has become one of the most deadly due to lifestyle changes and its widespread prevalence in many countries. Nevertheless, data analysis can prevent many deaths [1]. Therefore, diabetes is a major health issue in most developing countries, and the healthcare industry collects and processes huge amounts of medical data in different formats and sizes for people with diabetes [2]. The key feature of type-1 diabetes mellitus is the loss of the pancreatic islets of Langerhans' insulin-producing beta cells, resulting in insulin deficiency. This form can also be categorized as idiopathic or immune-mediated. Although type-1 diabetes can affect adults or children, most cases are immune-mediated, so the condition was once known as "juvenile diabetes" [3]. In this blood glucose system, the two most common terms used are hypoglycemia and hyperglycemia. Low blood sugar can cause a clinical condition called hypoglycemia, or low blood glucose. Each individual will experience hypoglycemic symptoms differently [4]. Traditionally, hypoglycemia is recognized by a low blood sugar level accompanied by symptoms that disappear as soon as the sugar level returns to normal. Short-term hypoglycemia can lead to diabetic coma or fainting. Insulin resistance or insufficient amounts of insulin are the main causes of high blood sugar. This results in diabetes. People with diabetes need to adjust their lifestyle and take medications such as synthetic insulin or oral diabetic supplements to maintain regular blood sugar levels.

Deep Learning (DL) algorithms have recently attracted considerable attention in academic circles and industry due to their successful application in a number of research areas, including voice recognition, natural language processing and brain-computer interface [5]. When developing Machine Learning (ML) and DL algorithms, the architecture of the learning model can be defined in different ways. A variety of options must be able to be explored, as it is often not known which is the best model architecture for a particular model. The machine should perform this investigation and automatically identify the ideal model structure in the ML and DL workflow [6]. Hyperparameters are the parameters that define the model's structure [7], so the term "hyperparameteroptimization" refers to the process of identifying the optimal model structure. Thus, the following are the contributions of this work:

DOI: 10.2478/msr-2024-0011

Correspondingauthor: kpriyaanilesh@gmail.com (K. Priyadarshini)

- Construction of switching Nonlinear Model Predictive Control (NMPC) systems for insulin and blood sugar regulation. Using the traditional open-loop step response technique, we first discovered different linear models at different operating points to develop a nonlinear controller.
- It consists of an insulin pump, a glucagon pump, a control algorithm and a Continuous Glucose Monitor (CGM). It is built using state-dependent limitations and a heuristic to switch between glucagon and insulin.
- The attention based Long Short-Term Memory (LSTM) considers various effects of features such as time-varying parameters, uncertainty cases and lack of sensitivity to glucose for the patient and controller in the present work.

The remaining parts of this paper are outlined below. Section 2 provides a description of the literature review. The proposed technique is described in Section 3. The performance and result analysis with comparative studies is discussed in Section 4. Section 5 outlines a conclusion and future work.

2. Related works

In this section you will find some controllers that had DL modes in the past. Based on the Dyna-Q Reinforcement Learning Algorithm (QRLA), Giorno et al. (2023) [8] have developed a fully automated glycemic management system that can autonomously determine the insulin infusion without the patient having to provide information about their carbohydrate intake (Llangarica et al., 2023) [9]. The Input and State Recurrent Kalman Network (ISRKN) integrates an input and state Kalman filter into the latent space of a deep neural network so that the posterior distributions can be computed in closed form and uncertainty can be communicated using Kalman equations. Furthermore, the developed architecture enables the explicit calculation of the meal uncertainty distribution, which is embedded in the filter parameters via a probabilistic controller. According to Taherinasab et al. (2022) [10], a modified Smith predictor and adaptive model reference control are combined to create a novel adaptive control structure for time-delayed systems. Model Predictive Control and Proportional-Integral-Derivative are modified to help TD1M patients control their blood glucose levels (Matamoros et al., 2021) [11]. To counteract the effects of food and exercise and prevent hypoglycemia, two control algorithms related to food intake and physical activity will be evaluated. An unmanned insulin delivery controller device based on a smartphone (Deshpande et al., 2022) [12] can help adolescents and youngsters adopt and utilize interoperable components. The standard deviation of overnight glucose was 43 mg/dL (compared to SAP 57.9 mg/dL, P = 0.009), while the coefficient of variance was 25.7% (compared to SAP 34.9%, P < 0.001). The percentage of time spent connected to the CGM and in closed-loop mode was 99.6% and 92.7%, respectively.

3. Proposed methodology

In this work, an extended mathematical patient model for the treatment of patients with type-1 Diabetic Mellitus is developed, called NMPC with Long Short-Term Memory (LSTM) (NMPC_LSTM). This management strategy uses both an insulin and a glucagon pump. The AP was developed with state-dependent limitations and a heuristic to switch between insulin and glucagon. We use a simpler model for control and add glucagon and exercise to an existing glucoregulatory model for simulation.

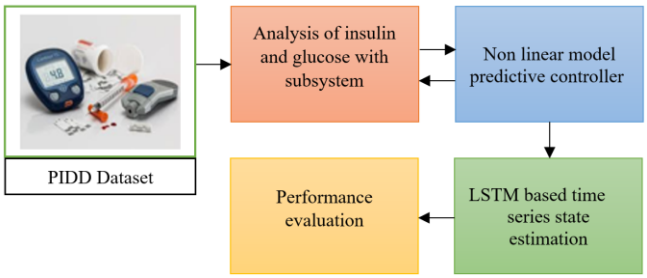

Fig. 1. Block diagram of the proposed methodology.

A. *Dataset description*

The Pima Indian Diabetes Dataset (PIDD) was collected fromkaggle (https://www.kaggle.com/uciml/pima-indians-diabetes-database), the world's largest community of data scientists and machine learners. The National Institute of Diabetes and Digestive and Kidney Diseases conducted the initial research on PIDD. The dataset's goal is to diagnose and predict whether or not a patient has diabetes based on certain diagnostic parameters included in the collection. These examples were chosen from a larger database under a number of restrictions. As a precaution, each patient is a girl of Pima Indian ancestry who is at least 21 years old. PIDD consists of a total of 768 samples, of which 268 are positive for DM, represented by *class 1* and 500 are negative for DM, represented by *class 0*, as described in the following attribute list:

1. The number of pregnancies.
2. An oral glucose tolerance test after two hours that measures plasma glucose concentration.
3. Diastolic blood pressure [mm/hg].
4. Skin fold thickness [mm] of the triceps.
5. Serum insulin [μU/ml] after two hours.
6. Body mass index [kg of weight / m of height].
7. The pedigree function of diabetes.
8. Years of age.

We calculated various summary statistics by considering the attribute values. For each attribute, these data are as follows: mean, standard deviation, minimum, 25%, 50%, 75% and maximum values.

B. *Nonlinear model predictive controller (NMPC)*

We use a NMPC, which is an extension of the Medtronic Virtual Patient (MVP) model expressed as a system of coupled stochastic differential equations. We extend it to include the meal and glucagon subsystems and represent the dynamics between glucose and insulin. The subsystem of insulin absorption consists of:

$$dI_{SC}(\mathrm{t}) = k_1\left(\frac{u_{ba}(t)+u_{bo}(t)}{c_I} - I_{SC}(t)\right)dt \quad (1)$$

$$dI_P(\mathrm{t}) = k_2(I_{SC}(t) - I_P(t)dt \quad (2)$$

where k_1 and k_2 indicate the glucose kinetics, $k_2 = k_1[1/min]$ is the inverse insulin absorption time constant, $C_l[L/min]$ is the insulin clearance rate and $I_{SC}[mU/L]$ is the subcutaneous insulin concentration. $I_P[mU/L]$ is the plasma insulin concentration. u_{ba} is the nominal basal rate and u_{bo} is the insulin bolus. The blood glucose level and insulin sensitivity are described by stochastic differential equations:

$$dI_{EEF}(t) = p_2\big(S_I(t)I_P(t) - I_{EEF}(t)\big)dt \tag{3}$$

$$dG(t) = [-\big(GEZI + I_{EFF}(t)\big)G(t) + EGP + R_A(t) + \\ + K_{glu}Q_2^G(t) + \sigma_G\sigma_S dG(t)] \tag{4}$$

where K_{glu} *is* the glucose kinetics. Q_2^G and Q_1^G are non-accessible and accessible compartments. The formula for insulin effect is $I_{EFF}[1/min]$, the inverse insulin action time constant is $p_2 = k_1[1/min]$, the insulin sensitivity is $S_I\left[\frac{\frac{L}{mU}}{min}\right]$, the glucose effectiveness is $GEZI[1, min]$, the endogenous glucose production is $EGP[\frac{mm}{L}]$, and the diffusion coefficients for glucose and insulin sensitivity are σ_G and σ_S. $R_A\,[\frac{mm}{min}]$, the meal rate of appearance, is:

$$R_A(t) = \frac{k_m D_2(t)}{V_G} \tag{5}$$

where k_m is the time constant, $D_2(t)$ is the meal system with respective time. Every five minutes, the glucose concentration in the blood is measured and sent to the NMPC algorithm. The following equations for the manual inputs are then solved using the Wiener to calculate a filtered approximation of the states used as initial states, x'_0.

$$\min_{[x(t).\{u_k\}^{N-1}]} \emptyset = \emptyset\,([x(t)]_{t_0}^{t_f},\ \{u_k\}_{k=0}^{N-1}) \tag{6}$$

Subject to,

$$x(t_0) = x'_0$$

$$x'(t) = f(t), x(t), u(t), d(t), \theta), \quad t \in [t_0, t_f] \tag{7}$$

$$u(t) = u_k, t \in [t_k, t_{k+1}], \quad k = 0, \ldots N-1 \tag{8}$$

$$d(t) = d'_k, t \in [t_k, t_{k+1}], \quad k = 0, \ldots N-1 \tag{9}$$

The forecast and control horizon $[t_0, t_f]$, is 6 hours and each of the N control intervals is five minutes long. $\emptyset$ indicates the concentration factor, $x(t)$ indicates input for prediction model and u_k indicates control interval. $f(t)$ indicates the filteration state and θ is the kinetic factor, $d(t)$ is the infinitesimal change of time. Fig. 2 shows that the horizon $[t_0, t_f]$ is shifted by one control interval and a new measurement is taken only after the first set of modified inputs, u_0 is delivered.

The administration of glucagon or insulin determines the objective function. In each instance, it has the form:

$$\emptyset = \int_{t_0}^{t_f} p_z\big(z(t)\big)dt + \sum_{k=0}^{N-1} p_u(u_k) \tag{10}$$

where the outputs p_z and p_u are penalty functions of the continuous glucose monitor if $z(t) = g(t, x(t), \theta)$, where z is the continuous glucose monitor.

The penalty function is:

$$p_z(z) = \alpha_z p_{z'}(z) + \alpha_{z(min)} p_{z(min)}(z) + \alpha_{z(max)} p_{z(max)}(z) \tag{11}$$

Firstly, the deviation of the blood glucose level from the set point, $z' = 6\ mm/L$, is penalized; secondly, $(z < z_{min} = \frac{4.5mm}{L})$ hypoglycemia and $(z > z_{max} = 10\ mm/L)$ penalizes hyperglycemia.

$$p_{z'}(z) = \frac{1}{2}(z - z')^2 \tag{11a}$$

$$p_{z(min)}(z) = \frac{1}{2}(min\ \{0, z - z_{min}\})^2 \tag{12}$$

$$p_{z(max)}(z) = \frac{1}{2}(max\ \{0, z - z_{max}\})^2 \tag{13}$$

The weights in (11) are $\alpha_z = 1$, $\alpha_{z(min)} = 10^6$, $\alpha_{z(max)} = 50$ when calculating the insulin flow rates and $\alpha_{z(min)} = 0$ when calculating the glucagon flow rate. It is obvious that the prevention of hypoglycemia has the highest priority.

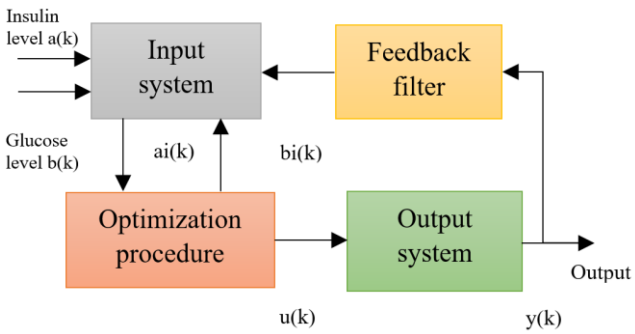

Fig. 2. Block diagram of NMPC.

C. *LSTM based time series state estimation*

To estimate the state of time series. To cope with learning from long-term dependencies, the LSTM uses a complex structure with numerous cells and gated units, such as:

$$f_t = \sigma(W_f[h_{(t-1)}, x_t] + b_f) \tag{14}$$

$$i_t = \sigma(W_i[h_{(t-1)}, x_t] + b_i) \tag{15}$$

$$C'_t = tanh(\,W_c[h_{(t-1)}, x_t] + b_C) \tag{16}$$

$$C_t = f_t \times C_{(t-1)} + i_t \times C'_t \tag{17}$$

$$o_t = \sigma(W_0[h_{(t-1)}, x_t] + b_0) \tag{18}$$

$$h_t = o_t \times tanh\,(C_t) \tag{19}$$

where f stands for the cell's forgetting gate, the weight W, the learning bias b and the sigmoid activation function σ, W_i is weight of input gate (14). The input gate, denoted by i in (15), is used in conjunction with a non-linear (tanh) layer C'. The new value of the cell state is C' (16). The standard state $C_{(t-1)}$ multiplied by f_t, which determines that it is ignored, and the created value C' multiplied by the input gate value is equal to the upgraded state value C (17). Finally, the sigmoid gate's output, o, is combined with the cell state C to determine whether or not patient x has type-1 diabetes, using (18) and (19).

4. Experimental results

The study was carried out with the Windows 10 operating system and an Intel Core CPU. The algorithm was developed and tested with Python version 3.7. The system used for the research includes 16GB DDR4 RAM, an NVIDIA GeForce GTX 1050 Ti SC 4GB GPU and an Intel i3-8100 CPU running at 3.6 GHz. The Stability analysis of the proposed model with different patient conditions was tested using the simulated datasets shown in Fig. 3. The normal, abnormal and critical condition of the patients was reported to the doctors based on the analysis of the standard deviation factor through an automatic indication.

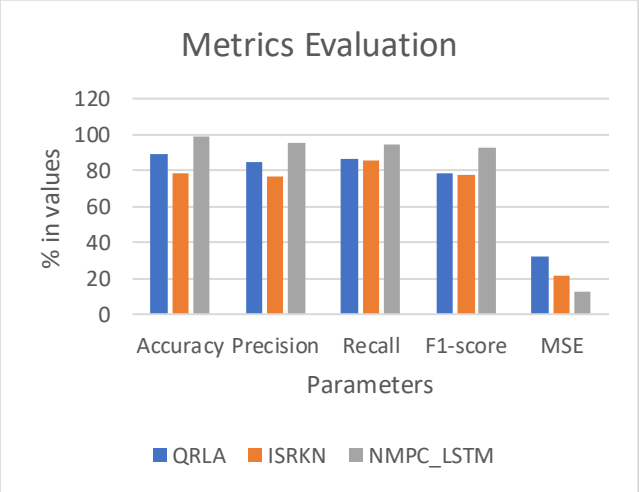

Fig. 3. Performance analysis of proposed method with existing methods.

In the following part, a brief overview of metrics such as accuracy, precision, recall, F1-score and mean square error is given before a comparative analysis with existing methods such as the QRLA [8] and ISRKN [9] is performed. Table 1 and Fig. 3 show the performance analysis between the existing method and the proposed method.

The comparative analysis table shows the performance evaluation of three different methods: QRLA, ISRKN and the proposed NMPC_LSTM, in terms of different parameters. In terms of accuracy, which measures the overall correctness of the predictions, the proposed NMPC_LSTM method significantly outperforms both QRLA and ISRKN, achieving an accuracy of 98.95% compared to 89.34% and 78.65%, respectively. This indicates that NMPC_LSTM makes the most accurate predictions among the three methods. The Precision of the proposed NMPC_LSTM is 95.68%, which is a significant value compared to the existing techniques of QRLA with84.34% and ISRKN with 76.43%.

Table 1. Comparative analysis between existing and proposed methods.

Parameters	QRLA	ISRKN	NMPC_LSTM
Accuracy	89.34	78.65	98.95
Precision	84.34	76.43	95.68
Recall	86.44	85.35	94.32
F1-score	78.47	77.46	92.50
MSE	32.45	21.46	12.45

For Recall, the proposed NMPC_LSTM leads with a value of 94.32%, which shows the effectiveness of the proposed method compared to QRLA and ISRKN, which achieve recall rates of 86.44% and 85.35%, respectively. The F1-score is the mean of precision and recall, where the proposed NMPC_LSTM achieves the highest F1-score of 92.5%, showing the good balance, while QRLA and ISRKN achieve 78.47% and 77.46%, respectively. Finally, Mean Square Error (MSE) indicates the difference between the predicted and actual values. The developed NMPC_LSTM outperforms QRLA and ISRKN with 12.45 compared to 32.45 and 21.46. Thus, the proposed NMPC_LSTM shows significant performance when analyzed with all metrics.

5. Conclusion

The proposed NMPC_LSTM is implemented to regulate blood glucose even in the presence of sudden fluctuations. The developed model is further validated, which shows that the accuracy rate has increased but the value of the mean square error has decreased. Simulation analysis shows that the settling time of the proposed model has been reduced to50 minutes compared to other recent adoptive controllers. The proposed method is also evaluated on simulated diabetes datasets achieving a higher accuracy of 98.95%, precision of 95.68%, recall value of 94.32%, F1-score value of 92.5, and MSE of 12.45%. The work will be extended in the future to include real-time design of a controller with optimization techniques and best feature selection methods to improve the performance of the generalization system and test cost-effective services for the real world.

Acknowledgment

The authors would like to thank the Deanship of Scientific Research at King Khalid University for funding this work as part of a large group Research Project under grant number (RGP2/134/44). Princess Nourah Bint Abdulrahman University Researchers Supporting Project number (PNURSP2024R719), Princess Nourah Bint Abdulrahman University, Riyadh, Saudi Arabia.

REFERENCES

[1] World Health Organization. (2016). *Global Report on Diabetes*. ISBN 978-92-4-156525-7.

[2] Tauschmann, M., Hovorka, R. (2018). Technology in the management of type 1 diabetes mellitus — current status and future prospects. *Nature Reviews Endocrinology*, 14, 464-475. https://doi.org/10.1038/s41574-018-0044-y

[3] Rachdaoui, N. (2020). Insulin: The friend and the foe in the development of type 2 diabetes mellitus. *International Journal of Molecular Sciences*, 21 (5), 1770. https://doi.org/10.3390/ijms21051770

[4] Felizardo, V., Garcia, N. M., Pombo, N., Megdiche, I. (2021). Data-based algorithms and models using diabetics real data for blood glucose and hypoglycaemia prediction - A systematic literature review. *Artificial Intelligence in Medicine*, 118, 102120. https://doi.org/10.1016/j.artmed.2021.102120

[5] Zhang, X., Yao, L., Sheng, Q. Z., Kanhere, S. S., Gu, T., Zhang, D. (2018). Converting your thoughts to texts: Enabling brain typing via deep feature learning of EEG signals. In *IEEE International Conference on Pervasive Computing and Communications (PerCom)*. IEEE. https://doi.org/10.1109/PERCOM.2018.8444575

[6] Gopalun, G., Samuvel, D. J. (2023). Deep learning technique for power domain non-orthogonal multiple access using optimised LSTM in cooperative networks. *Technical Gazette*, 30 (5), 1397-1403. https://doi.org/10.17559/TV-20221228104420

[7] Jayanthi, J., Jayasankar, T., Krishnaraj, N., Prakash, N. B., Sagai Francis Britto, A., Vinoth Kumar, K. (2021). An intelligent particle swarm optimization with convolutional neural network for diabetic retinopathy classification model. *Journal of Medical Imaging and Health Informatics*, 11 (3), 803-809. https://doi.org/10.1166/jmihi.2021.3362

[8] Del Giorno, S., D'Antoni, F., Piemonte, V., Merone, M. (2023). A New Glycemic closed-loop control based on Dyna-Q for Type-1-Diabetes. *Biomedical Signal Processing and Control*, 81, 104492. https://doi.org/10.1016/j.bspc.2022.104492

[9] Langarica, S., Rodriguez-Fernandez, M., Doyle III, F. J., Núñez, F. (2023). A probabilistic approach to blood glucose prediction in type 1 diabetes under meal uncertainties. *IEEE Journal of Biomedical and Health Informatics*, 27 (10), 5054-5065. https://doi.org/10.1109/JBHI.2023.3309302

[10] Taherinasab, S., Soleimaniasl, S., Taherinasab, S. (2022). Application of model reference adaptive control and modified Smith predictor to control blood glucose in type 1 diabetic patients. *Mathematics and Computers in Simulation*, 194, 198-209. https://doi.org/10.1016/j.matcom.2021.05.033

[11] Matamoros-Alcivar, E., Ascencio-Lino, T., Fonseca, R., Villalba-Meneses, G., Tirado-Espín, A., Barona, L., Almeida-Galárraga, D. (2021). Implementation of MPC and PID control algorithms to the artificial pancreas for diabetes mellitus type 1. In *2021 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT)*. IEEE. https://doi.org/10.1109/ICMLANT53170.2021.9690529

[12] Deshpande, S., Weinzimer, S. A., Gibbons, K., Nally, L. M., Weyman, K., Carria, L., Zgorski, M., Laffel, L. M., Doyle, F. J., Dassau, E. (2022). Feasibility and preliminary safety of smartphone-based automated insulin delivery in adolescents and children with type 1 diabetes. *Journal of Diabetes Science and Technology*, 18 (2). https://doi.org/10.1177/19322968221116384

Received September 18, 2023
Accepted March 12, 2024