Poster: Glysigma: Personalized Glucose Forecasting Enhanced by Bayesian Optimization on CGM Data

Pegah Khorasani, Saman Khamesian, Abdullah Mamun, and Hassan Ghasemzadeh

***Abstract*—Although Continuous Glucose Monitoring (CGM) devices are crucial for managing diabetes by providing real-time blood glucose measurements, the variability in glycemic thresholds among individuals makes it challenging to forecast blood glucose. Accurate forecasting of glucose levels can improve diabetes management and prevent dysglycemia. This study proposes Glysigma, a system for forecasting blood glucose levels. This system uses a CGM device, a smartphone app, and a machine learning tool called Glysigma Predictor for processing and forecasting CGM data. Our system uses Bayesian optimization to tailor glucose prediction models to individual patients. We also propose a custom loss function that uses personalized thresholds and different weights for errors in normal and dysglycemic ranges. With the support of Bayesian optimization, our LSTM-based prediction model can forecast glucose levels in advance. Our system was tested on the OhioT1DM dataset it predicted future blood glucose effectively with an MAE of 12.67.**

***Index Terms*—continuous glucose monitoring, glycemic threshold, bayesian optimization, diabetes management**

I. Introduction

An accurate forecast of blood glucose levels can help better diabetes management and prevent unwanted outcomes. Dysglycemic thresholds define the blood glucose levels that can trigger specific clinical symptoms. Different patients may have different thresholds for hypo- and hyperglycemia, affected by age, health conditions, medications, lifestyle, etc. [1].

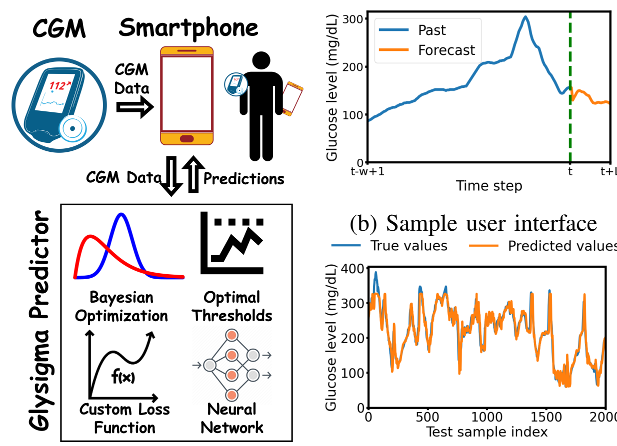
In this work, we propose a system, Glysigma, that has a continuous glucose monitoring (CGM) wearable, a smartphone app, and a machine learning system for forecasting blood glucose levels. Fig. 1a and Fig. 1b illustrate the system and its user interface (UI). The UI displays the recent blood glucose and a prediction of the upcoming glucose levels. The Glysigma Predictor of Fig 1a was implemented with Bayesian optimization, custom loss function, and an LSTM-based forecasting model and tested on the OhioT1DM dataset. Glucose was measured in this dataset once every 5 minutes. Our system first separates training and test data and then creates sliding windows of 150 minutes. The target variable is the glucose level 30 minutes from the current time.

Our custom loss function prioritizes critical ranges of hypoglycemia and hyperglycemia, assigning different weights to errors depending on whether the glucose level is dysglycemic.

$$\mathrm{Loss}(y_{\text{true}}, y_{\text{pred}}) = \begin{cases} \text{Hypo Weight} \times (y_{\text{true}} - y_{\text{pred}})^2 & \text{if } y_{\text{true}} < \text{Hypo Threshold}, \\ \text{Hyper Weight} \times (y_{\text{true}} - y_{\text{pred}})^2 & \text{if } y_{\text{true}} > \text{Hyper Threshold}, \\ \text{Normal Weight} \times (y_{\text{true}} - y_{\text{pred}})^2 & \text{otherwise.} \end{cases}$$

Authors are with the College of Health Solutions, Arizona State University, Phoenix, AZ 85054, USA.

Emails: {pkhorasa, skhamesi, a.mamun, hassan.ghasemzadeh}@asu.edu



(a) Glysigma system

(b) Sample user interface

(c) Results on test set

Fig. 1: System overview, sample user interface, and results of the Glysigma system. In (b), t = current time step, w = size of the sliding window, L = prediction horizon.

These thresholds and weights were optimized for each patient using Bayesian optimization, ensuring the model is more sensitive to critical glycemic events, thus improving prediction performance based on Root Mean Squared Error (RMSE). Based on this approach, hyperparameter tuning is viewed as a black box, derivative-free optimization problem since no precise mathematical function is available to describe the relationship between hyperparameters and model performance. Using a probabilistic model, Bayesian optimization directs the search for optimal parameters, balancing exploration and exploitation. In this process, the parameters are adjusted iteratively to personalize glucose management.

In our experiments for this pilot study, optimal thresholds were searched with Bayesian optimization for hypoglycemia between 60 and 85 mg/dL, and for hyperglycemia between 190 and 240 mg/dL. Based on the custom loss function with optimal thresholds and weights, Our LSTM-based model was able to forecast glucose levels 30 minutes in advance with an RMSE of 18.3 and MAE of 12.67. We compare the real and the predicted glucose levels of the test data in Fig. 1c, where we notice that our model's prediction is very close to the ground truth values in most cases.

References

[1] A. D. Association, "6. glycemic targets: standards of medical care in diabetes—2021," *Diabetes care*, vol. 44, no. Supplement_1, pp. S73–S84, 2021.