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

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INTRODUCTION

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.

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].

These thresholds and weights were optimized for each patient through Bayesian optimization, enhancing the model's sensitivity to critical glycemic events and improving prediction performance. This method treats hyperparameter tuning as a black box, derivative-free optimization problem, as there is no exact mathematical function to define the relationship between hyperparameters and model performance.

By utilizing a probabilistic model, Bayesian optimization efficiently guides the search for optimal parameters, balancing exploration and exploitation. This iterative process adjusts the parameters to personalize glucose management effectively.

METHODOLOGY

In this study, we introduce Glysigma, a comprehensive system comprising a continuous glucose monitoring (CGM) wearable device, a smartphone application, and a machine learning model for predicting blood glucose levels.

Fig. 1 depicts the system and its user interface (UI) within the smartphone app, which shows the latest blood glucose measurements along with forecasts for future levels. The Glysigma Predictor illustrated in Fig. 1 was designed using Bayesian optimization, a custom loss function, and an LSTM-based forecasting model. Our custom loss function (1) emphasizes critical ranges of hypoglycemia and hyperglycemia by assigning varying weights to errors based on whether the glucose levels fall into Dysglycemic categories.

$$\text{Loss}(y_{\text{true}}, y_{\text{pred}}) = \begin{cases} \text{Hypo Weight} \times (y_{\text{true}} - y_{\text{pred}})^2 & \text{if } y_{\text{true}} < \text{Hypo Threshold}, \\ \text{Hyper Weight} \times (y_{\text{true}} - y_{\text{pred}})^2 & \text{if } y_{\text{true}} > \text{Hyper Threshold}, \\ \text{Normal Weight} \times (y_{\text{true}} - y_{\text{pred}})^2 & \text{otherwise.} \end{cases} \tag{1}$$

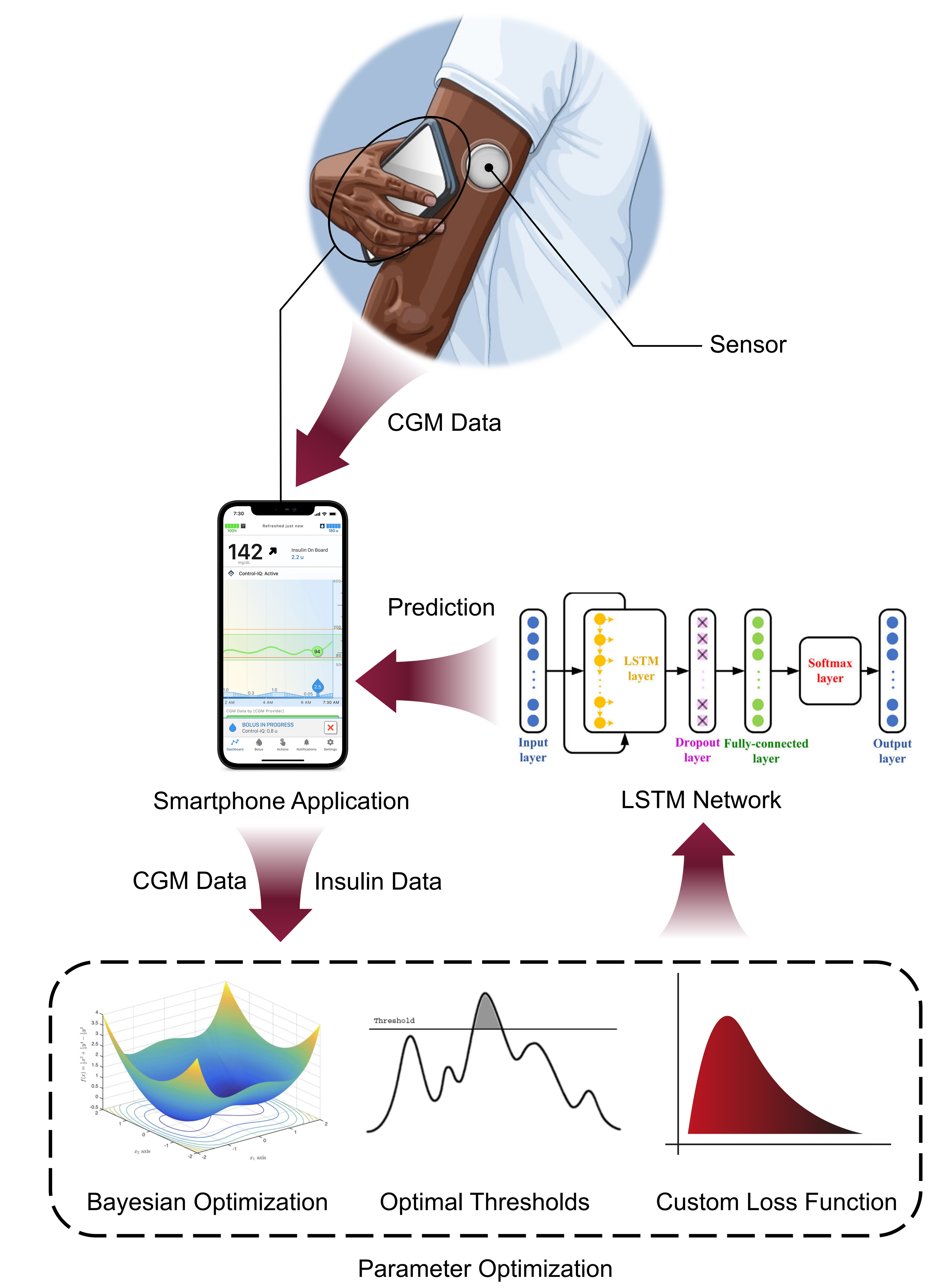

Fig. 1. Glysigma System

DATASET

The dataset used for testing is the OhioT1DM dataset [2], which includes glucose level measurements taken every 5 minutes. Initially, we divide the data into training and testing sets. Subsequently, we generate sliding windows of 150 minutes each. The target variable for our analysis is the glucose level recorded 30 minutes after the current time.

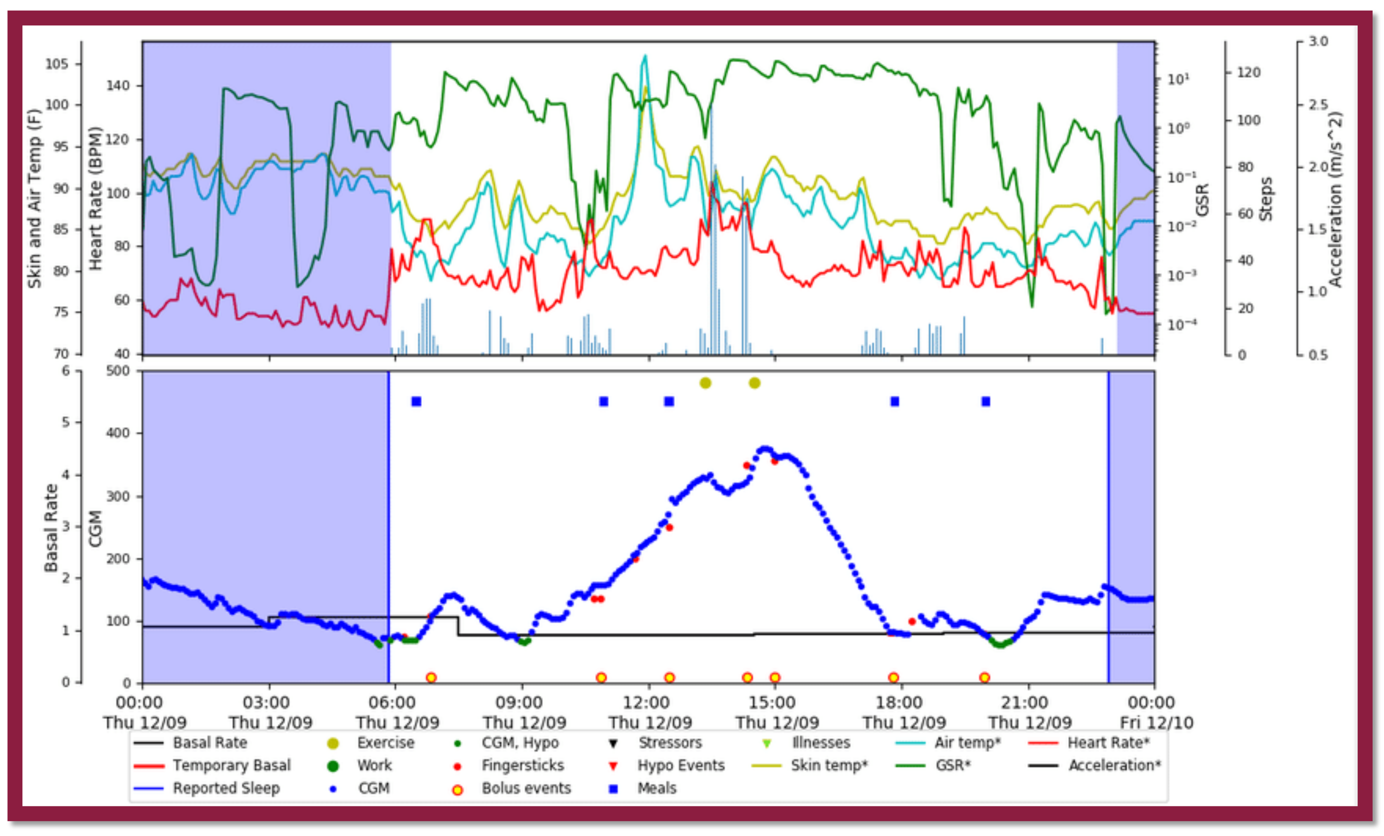

Fig. 2. OhioT1DM 2020 dataset overview for patient ID 591

RESULTS

In our pilot study experiments, we utilized Bayesian optimization to identify optimal thresholds for hypoglycemia, ranging from 60 to 85 mg/dL, and for hyperglycemia, between 190 and 240 mg/dL. Leveraging a custom loss function with these optimal thresholds and weights, our LSTM-based model successfully predicted glucose levels 30 minutes in advance, achieving a root mean squared error (RMSE) of 18.3 mg/dL and a mean absolute error (MAE) of 12.67 mg/dL.

CONCLUSION

In conclusion, the Glysigma system offers a promising solution for personalized glucose forecasting by integrating CGM data with advanced machine learning techniques. Utilizing Bayesian optimization for tailored model parameters, Glysigma effectively addresses variability in glycemic thresholds. The custom loss function prioritizes critical ranges, leading to enhanced predictive performance. Our results indicate that the LSTM-based model can forecast glucose levels 30 minutes in advance, achieving an MAE of 12.67 mg/dL. Overall, Glysigma represents a significant advancement in personalized diabetes management, potentially improving patient outcomes.

REFERENCES

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