GlucoseAssist: Personalized Blood Glucose Level Predictions and Early Dysglycemia Detection

Prisha Shroff, Asiful Arefeen, Hassan Ghasemzadeh

***Abstract*—Regulating blood glucose concentration is crucial for all people, particularly for patients with diabetes or prediabetes to manage their metabolic health. Poor glucose control results in dysglycemia. Frequent dysglycemia exposure increases the risk of cardiovascular disease, seizures, loss of consciousness, and potentially death. Patients often struggle with glucose control due to a multitude of interrelated behavioral, physiological, and biological factors such as diet, insulin intake, and metabolism rate. There is a need for a solution that can accurately predict future adverse dysglycemic events and important parameters such as the area under the glucose curve (AUC). However, current research uses limited input parameters, lacks potential meal-based predictions, is data-hungry and computationally expensive, and predicts a single health outcome. In this research, *GlucoseAssist*[1], a novel, personalized, AI-driven system was developed to predict glucose response and area under the glucose curve in real-time and identify dysglycemic events based on diet, health, and medication data. Importantly, the devised tiered architecture uses a multimodal convolutional neural network and random forest classifier with time series data from a clinical dataset with $20,040$ Continuous Glucose Monitor (CGM) records. GlucoseAssist accurately predicts blood glucose response for the next 30 minutes with a Root Mean Squared Error of 1.23 mmol/L, Mean Absolute Error of 0.920 mmol/L, and an accuracy of 97.1%.**

***Index Terms*—deep learning, diabetes, forecasting, hyperglycemia, wearables**

I. Introduction

As of 2021, over 537 million people globally suffer from diabetes, and 374 million suffer from prediabetes. Diabetes is prevalent among the youth as well. The American Diabetes Association estimates that more than half a million young people could have diabetes by 2060, a 700% increase from today. One in three Americans have prediabetes, and one in seven has diabetes, making this a large national issue [1].

Lack of glucose management is one of the world's most rapidly growing health problems, which leads to dysglycemic events such as postprandial hyperglycemia and reactive hypoglycemia [2]. Postprandial hyperglycemia is abnormal spikes in blood glucose levels after the consumption of a meal. Effects of postprandial hyperglycemia include diabetic retinopathy, vascular dementia, nerve damage, cardiovascular diseases, kidney disease, diabetic ketoacidosis, and diabetic neuropathy. Repeated exposure to postprandial hyperglycemia is connected to several health disorders like prediabetes, diabetes, atherosclerosis, and obesity [3]. Reactive hypoglycemia is an unnatural drop in glucose levels. Multiple occurrences of reactive hypoglycemia lead to confusion, loss of coordination, slurred speech, and blurry vision. During severe cases, hypoglycemia can lead to seizures, loss of consciousness, higher risk of heart disease and potentially death [4].

The utilization of CGMs to track blood glucose levels is growing. CGMs measure glucose amounts in the bloodstream at constant intervals and transmit the information to a monitor for real-time viewing. Although CGMs can display blood glucose data in real-time, they lack computational capabilities to warn the user of future dysglycemic events, inhibiting the user from taking preventative action. Previously, research was conducted to use CGM data to detect hyperglycemic events with interpretations [5], simulate glucose response using deep learning [6], and predict blood glucose levels using a recurrent neural network (RNN) that took both glucose and insulin information as input [7]. Drawbacks of utilizing an RNN includes its inability to learn long-term dependencies. Prendin [8] developed a unique solution using RNN, it did not take other parameters as input and disregarded the time steps associated with the values. Mathiyazhagan et al. [9] combined an adaptive network with a fuzzy inference system to predict BG responses. However, the model only used data from 2 patients which led to overfitting. Aliberti [10] and Frandes [11] used a non-linear autoregressive neural network that could not predict dysglycemic events.

We propose a novel approach that uses a tiered AI architecture for the simultaneous prediction of hyperglycemia and estimation of the area under the glucose curve. The two-layer architecture uses (1) a convolutional neural network (CNN) for accurate prediction of postprandial glucose response from which the AUC is estimated; and (2) a random forest algorithm that takes the predicted glucose values and infers the glycemic state of the glucose response (i.e., normal versus hyperglycemia).

II. GlucoseAssist Design

GlucoseAssist works in two steps: forecasting and detecting. Fig. 1 shows a high-level diagram of the proposed pipeline. A unique aspect of GlucoseAssist is its multimodel approach. Within the pipeline, there needs to be two intelligent frameworks to map future blood glucose levels and to detect incoming abnormalities using the forecasted values. Let $X = \{x_1, x_2, ..., x_n\}$ be a set of n features that

This work was supported in part by the National Science Foundation, under grants CNS-2210133. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding organizations.

Prisha Shroff is with Hamilton High School, Chandler, AZ. She was a SCENE intern at ASU during the 2022-2023 academic year.

Asiful Arefreen and Hassan Ghasemzadeh are with the College of Health Solutions, Arizona State University, Phoenix, AZ.

email: prishashroff@gmail.com, {aarefeen, hassan.ghasemzadeh}@asu.edu

[1]Resources available at: https://github.com/prishashroff/GlucoseAssist

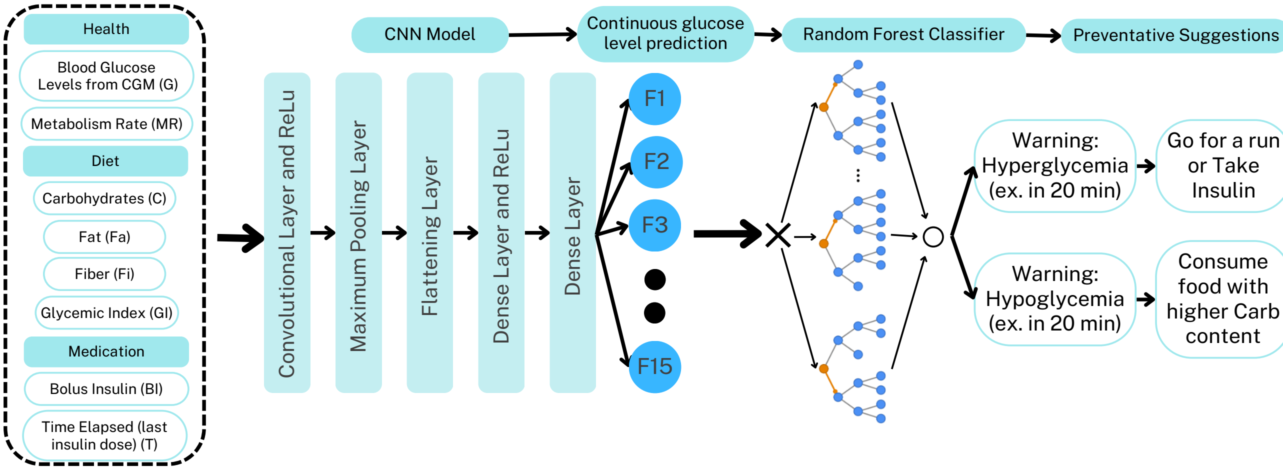

Fig. 1. High-level overview of GlucoseAssist. It consists of a CNN model followed by a Random Forest classifier.

provide retrospective information for a timeseries. The aim is to forecast the timeseries for a specific prediction horizon t i.e. $F = \{F_1, F_2, ..., F_t\}$. To do that, a forecasting model f needs to be trained in such a way that, if fed with desired data X, it can map the future t values of F.

$$f : \mathbb{R}^n \rightarrow \mathbb{R}^t \tag{1}$$

Here, $\mathbb{R}^n$ represents the n input features while $\mathbb{R}^t$ represents the t-timestamps long output sequence.

Furthermore, using the forecasted blood glucose level values, another machine learning model needs to be trained to determine the occurrence of dysglycemia. Let's denote the predicted dysglycemia labels as $z = \{z_1, z_2, ...\}$, where z_i is a ternary variable that represents hypoglycemia (0), normal (1) and dysglycemia (2) based on the blood glucose level prediction.

A. Forecasting Model

Personal diet, medication, and health data are sensitive information and their availability with proper annotation is often limited. However, CNN models offer advantages over models like LSTM, as they can perform well even with small datasets and exhibit noise resistance, ensuring improved model performance.

For forecasting future glucose levels, a CNN architecture comprising of four unique layers (Fig. 1) was developed. The first layer is the convolutional layer and is responsible for extracting high-level features by adjusting the weights ($\mathbf{W}_{conv}$) and biases ($\mathbf{b}_{conv}$). The output feature map is obtained by applying the Rectified Linear Unit (ReLU) activation function. Mathematically, the output can be represented as:

$$\mathbf{h}_{conv} = \text{ReLU}(\mathbf{W}_{conv} * X + \mathbf{b}_{conv}) \tag{2}$$

Following the convolutional layer, the maximum pooling layer enhances the robustness of the model. This layer performs fuzzy operations by selecting the maximum values from the dataset, reducing noise, and preventing overfitting. Later, the flattening layer is placed to reduce the dimensionality of the data, preparing it for further processing in the dense layer. The dense layer performs matrix multiplication operations to process the data and generates the final prediction results.

B. Detection Model

Random forest classifiers are utilized for binary and ternary classification. A random forest classifier uses a series of decision trees, which start from a root node. The root node breaks out into decision nodes, a split point that uses evaluations to create leaf nodes, the consequences of the decision.

As shown in Fig. 1, GlucoseAssist takes the user's health data (blood glucose levels from a CGM and metabolism rate), diet data (carbohydrates, fat, fiber, and glycemic index), and medication data (bolus insulin amounts and time elapsed since last insulin dose) from the last 60 minutes as input. Then, a CNN model predicts the user's blood glucose levels for the next 30 minutes. Utilizing a random forest classifier, GlucoseAssist notifies the user of future hyperglycemic or hypoglycemic events along with timestamps of the occurrence. It includes an intervention aspect that supplies the user with preventative feedback. For example, if the individual is predicted to have a hyperglycemic event, GlucoseAssist will recommend the user go for a run.

To summarize, GlucoseAssist initiates step 2 by leveraging the forecasted results from step 1 and detects if an abnormal event is forthcoming. If there is a hyperglycemic event impending, GlucoseAssist provides the user with another meal option with a lower carbohydrate value.

III. Experimental Results

A. Dataset

The Nutrient Absorption dataset [12] was used to train GlucoseAssist. This dataset contains $20,040$ CGM records of 167 meals from 5 patients (4 T2DM, 1T1DM, 4 males, 1 female, Ages: 35 ± 15.18). Subjects' dietary information (carb, fat, fiber amounts, and glycemic index) from individual meals, health data (individual's metabolism rate and 4-hour long postprandial CGM sequences captured at two-minute intervals), and medication data (consisting of the bolus insulin amounts and time elapsed since the last insulin dose) are readily available within the dataset. Data Preprocessing involved applying a sliding window on the multivariate data sequences of over 4 hours, splitting it into samples of 60 minutes of input and 30 minutes of output. The dataset was reshaped into a 3D array of samples, timesteps, and features, utilizing an automated framework we developed. The data was split into 80% training and 20% testing.

B. Hyperparameter Tuning

Several hyperparameters were tuned to predict future glucose levels accurately. The Conv1D layer had 240 filters, a kernel size of 2, and ReLU activation. The MaxPool layer had a pool size of 2 followed by a flattening layer. Afterward, there was a Dense Layer with 50 units and Relu activation. Following that, there was another Dense layer with 15 units. Adam Optimizer was used, and the model was run for 100 epochs.

The Random Forest Classifier was tuned using the Grid Search method. Based on that, a maximum tree depth of 3, minimum leaf samples of 3, 1 maximum feature and 200 n_estimators were determined to be the optimal hyperparameters. Tuning hyperparameters allowed us to avoid underfitting and overfitting while obtaining the highest accuracy.

C. Result Analysis

Standard analysis metrics were used to quantify the performance of GlucoseAssist including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R^2, accuracy, confusion matrix and Clarke Error Grid. The formulas are denoted below:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad \text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

TABLE I
RMSE, MAE AND R^2 (MMOL/L) OF BLOOD GLUCOSE LEVEL PREDICTIONS FOR A 30-MINUTE PREDICTION HORIZON USING CNN

CNN	Avg. P1	Avg. P2	Avg. P3	Avg. P4	Avg. P5	Average (30 min)
RMSE	1.52	1.163	1.15	1.426	0.888	1.23
MAE	1.09	0.894	0.884	1.033	0.698	0.92
R^2	0.801	0.783	0.874	0.706	0.922	0.817

TABLE II
RMSE, MAE AND R^2 (MMOL/L) OF BLOOD GLUCOSE LEVEL PREDICTIONS FOR A 30-MINUTE PREDICTION HORIZON USING LSTM

LSTM	Avg. P1	Avg. P2	Avg. P3	Avg. P4	Avg. P5	Average (30 min)
RMSE	2.798	2.222	3.039	2.390	2.487	2.587
MAE	2.194	1.721	1.965	1.64	2.05	1.914
R^2	0.319	0.199	0.181	0.172	0.364	0.247

The RMSE was calculated by taking the average of 5 trials for each subject and calculating the mean of those averages. Forecasting performance was evaluated using the test dataset. The CNN attained an RMSE of 1.230 and an MAE of 0.92 (Table I), which are 53% and 52% better than those of the LSTM (Table II). Therefore, we moved ahead with the CNN network for forecasting.

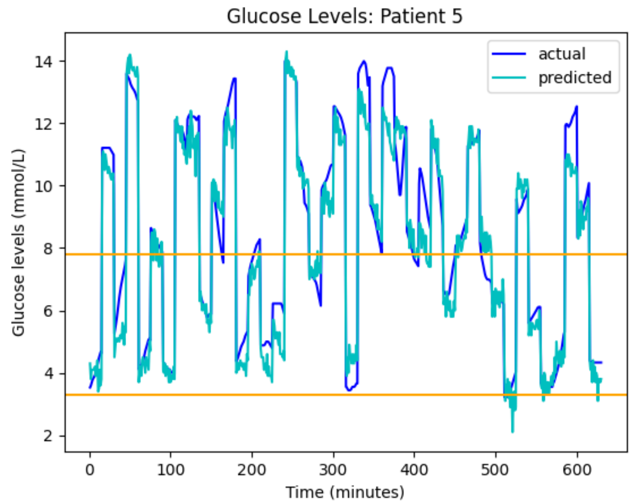

Fig. 2. Glucose levels Actual vs Predicted Patient 5

Fig. 2 demonstrates the actual vs predicted blood glucose levels for patients 5. The orange line at 7.8 mmol/L is the standard hyperglycemic threshold, and the line at 3.3 mmol/L is considered the standard hypoglycemic threshold. It was noticed that the model was able to accurately identify the hyperglycemic and hypoglycemic events, however, there is a need for a slight fine-tuning.

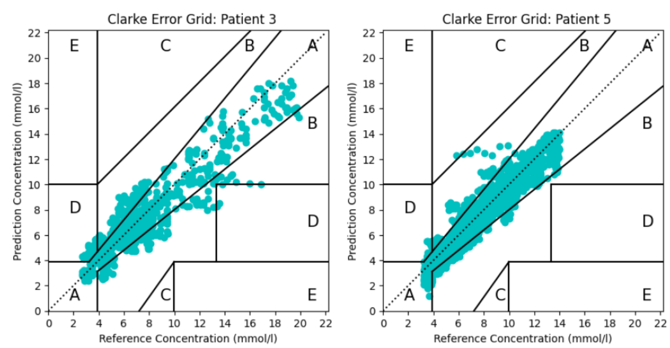

Fig. 3. Clarke Error Grid comparison of Patient 3 and Patient 5

Clarke's Error grid demonstrated the difference between the actual values and predicted values of GlucoseAssist. As seen in Fig. 3, most values fell between A and B, which are clinically accurate and clinically acceptable values, respectively. As observed in the Clarke Error Grids, there were no values in Zone C (overcorrecting) or E (erroneous treatment). Erroneous Treatment would lead to incorrect feedback. Furthermore, there were minimal values in Zone D, where dysglycemic events went undetected.

The results of the predicted AUC were compared to the values of the actual AUC [13] (Table III). The average values were very similar to each other (actual = 110.85 and predicted = 110.95), which demonstrates GlucoseAssist's accuracy.

TABLE III
AUC (MMOL/L-MINUTE) OF BLOOD GLUCOSE LEVEL PREDICTIONS FOR A 30-MINUTE PREDICTION HORIZON USING CNN

CNN	Avg. P1	Avg. P2	Avg. P3	Avg. P4	Avg. P5	Avg. All Patients
AUC (Actual)	108.97	114.31	99.81	114.03	117.14	110.85
AUC (Predicted)	108.89	118.31	98.01	112.54	116.99	110.95

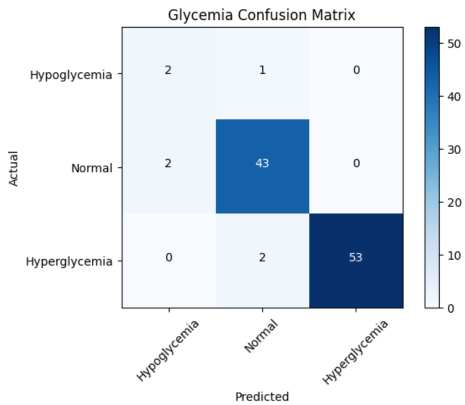

Fig. 4. Random Forest Classifier Confusion Matrix depicts the true positives, true negatives, false positives, and false negatives.

After the blood glucose levels were predicted, a random forest model was used to identify hyperglycemic and hypoglycemic events (Fig. 4). The classifier predicted the events correctly, with a 97.07% accuracy when analyzing data from all patients. As seen in the confusion matrix, there were more occurrences of hyperglycemia as the dataset was collected after a meal.

IV. Discussion and Conclusion

We designed a multimodal CNN model that predicts blood glucose response in real-time for a potential meal and detects dysglycemic events beforehand based on diet, health, and medication data. With 30-minute prediction horizon, GlucoseAssist utilizes advanced machine learning techniques including neural-network-based regression and classification techniques to accurately predict the glucose response with a nominal MAE of 0.92 mmol/L, RMSE of 1.23 mmol/L, and a 97.07% glycemic event identification accuracy. GlucoseAssist demonstrates the feasibility of developing a solution that makes accurate predictions with a limited training dataset size. The long prediction horizon leaves room for lifestyle changes.

The current research on computational modeling of human health based on CGM data uses limited input parameters and lacks potential meal-based predictions. In most cases, the models are data-hungry and computationally expensive, making user-friendly implementations with embedded systems difficult. The proposed solution can potentially help individuals manage their blood glucose levels more effectively. The developed technology predicts future blood glucose levels based on a potential meal, health and medication data, and this is used to estimate the AUC. Based on this information, the system can notify the user of potential dysglycemic events and suggest preventive measures.

Our future work will focus on enhancing the robustness of the developed machine learning algorithms for use in uncontrolled environments [14], designing solutions to dietary assessment [15] using passive sensing data such as continuous glucose monitor data, and deployment of the technology in clinical studies. Additionally, we are currently working on designing algorithms that use the prediction outcomes to automate the process of behavioral feedback delivery.

References

[1] H. Sun, P. Saeedi, S. Karuranga, M. Pinkepank, K. Ogurtsova, B. B. Duncan, C. Stein, A. Basit, J. C. N. Chan, J. C. Mbanya, M. E. Pavkov, A. Ramachandaran, S. H. Wild, S. James, W. H. Herman, P. Zhang, C. Bommer, S. Kuo, E. J. Boyko, and D. J. Magliano, "Idf diabetes atlas: Global, regional and country-level diabetes prevalence estimates for 2021 and projections for 2045," *Diabetes Research and Clinical Practice*, 2021.

[2] S. A. Tabish, "Is diabetes becoming the biggest epidemic of the twenty-first century?" *International journal of health sciences*, vol. 1 2, pp. V–VIII, 2007.

[3] M. Laakso, "Cardiovascular Disease in Type 2 Diabetes From Population to Man to Mechanisms: The Kelly West Award Lecture 2008," *Diabetes Care*, vol. 33, no. 2, pp. 442–449, 02 2010.

[4] E. Schuster and L. Zimmerman, "A guide to help consumers choose apps and avoid app overload." *The Journal of Extension*, vol. 52, 2014.

[5] A. Arefeen, S. N. Fessler, C. Johnston, and H. Ghasemzadeh, "Forewarning postprandial hyperglycemia with interpretations using machine learning," *2022 IEEE-EMBS International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, pp. 1–4, 2022.

[6] A. Arefeen and H. Ghasemzadeh, "Glysim: Modeling and simulating glycemic response for behavioral lifestyle interventions," in *IEEE EMBS International Conference on Biomedical and Health Informatics (BHI)*, 2023.

[7] E. Daskalaki, A. Prountzou, P. Diem, and S. G. Mougiakakou, "Real-time adaptive models for the personalized prediction of glycemic profile in type 1 diabetes patients." *Diabetes technology & therapeutics*, vol. 14 2, pp. 168–74, 2012.

[8] F. Prendin, S. D. Favero, M. Vettoretti, G. Sparacino, and A. Facchinetti, "Forecasting of glucose levels and hypoglycemic events: Head-to-head comparison of linear and nonlinear data-driven algorithms based on continuous glucose monitoring data only," *Sensors (Basel, Switzerland)*, vol. 21, 2021.

[9] N. Mathiyazhagan and H. B. Schechter, "Soft computing approach for predictive blood glucose management using a fuzzy neural network," *2014 IEEE Conference on Norbert Wiener in the 21st Century (21CW)*, pp. 1–3, 2014.

[10] A. Aliberti, I. Pupillo, S. Terna, E. Macii, S. Di Cataldo, E. Patti, and A. Acquaviva, "A multi-patient data-driven approach to blood glucose prediction," *IEEE Access*, vol. 7, pp. 69 311–69 325, 2019.

[11] M. Frandeș, B. Timar, and D. Lungeanu, "A risk based neural network approach for predictive modeling of blood glucose dynamics," *Studies in health technology and informatics*, vol. 228, pp. 577–81, 2016.

[12] R. A. H. Karim, I. Vassányi, and I. Kósa, "After-meal blood glucose level prediction using an absorption model for neural network training," *Computers in biology and medicine*, vol. 125, p. 103956, 2020.

[13] K. Sakaguchi, K. Takeda, M. Maeda, W. Ogawa, T. Sato, S. Okada, Y. Ohnishi, H. Nakajima, and A. Kashiwagi, "Glucose area under the curve during oral glucose tolerance test as an index of glucose intolerance," *Diabetology International*, vol. 7, pp. 53–58, 2016.

[14] S. A. Rokni and H. Ghasemzadeh, "Plug-n-learn: automatic learning of computational algorithms in human-centered internet-of-things applications," in *Proceedings of the 53rd Annual Design Automation Conference*, 2016, pp. 1–6.

[15] N. Hezarjaribi, S. Mazrouee, and H. Ghasemzadeh, "Speech2health: a mobile framework for monitoring dietary composition from spoken data," *IEEE journal of biomedical and health informatics*, vol. 22, no. 1, pp. 252–264, 2017.