128: Impact of Food on A Transformer Based Glucose Prediction Model to Predict Glucose Trajectories at Different Time Horizons

Junjie Luo, MS[2], Abhimanyu Kumbara, MS[1], Mansur Shomali, MD, CM[1], Anand Iyer, PhD[1], Gordon Gao[2], PhD
[1]Welldoc, Columbia, Maryland,USA,[2]Center for Digital Health and Artificial Intelligence, Johns Hopkins Carey Business School, Baltimore, MD,USA

BACKGROUND AND AIMS

Automated coaching based on accurate glucose predictions is important to and can help improve the self-management of diabetes[1]. Just as LEDs, digital temperature sensors, and accelerometers in activity trackers enable dense data collection of biometric signals such as heart rate, blood oxygen levels, skin temperature, movement/activity, and real-time sensors like continuous glucose monitoring (CGM) enable collection of dense glucose data.

There are many covariates—such as food, activity, and medications—that can impact glucose levels, and dense data from CGM allows us to quantitatively measure such impacts, which can then unlock glucose prediction capabilities. In Shomali et al. (2024), the authors showed that transformer-based large sensor models (LSM) can accurately predict glucose levels at 30 minutes, 60 minutes, and 2-hour intervals[2].

In this study, we built a transformer-based "large health model" (LHM) to study the additional impact of food on glucose prediction at 30 minutes, 60 minutes, and 2-hour intervals. The LHM takes glucose along with other covariates such as food consumed as inputs to more accurately predict future glucose levels.

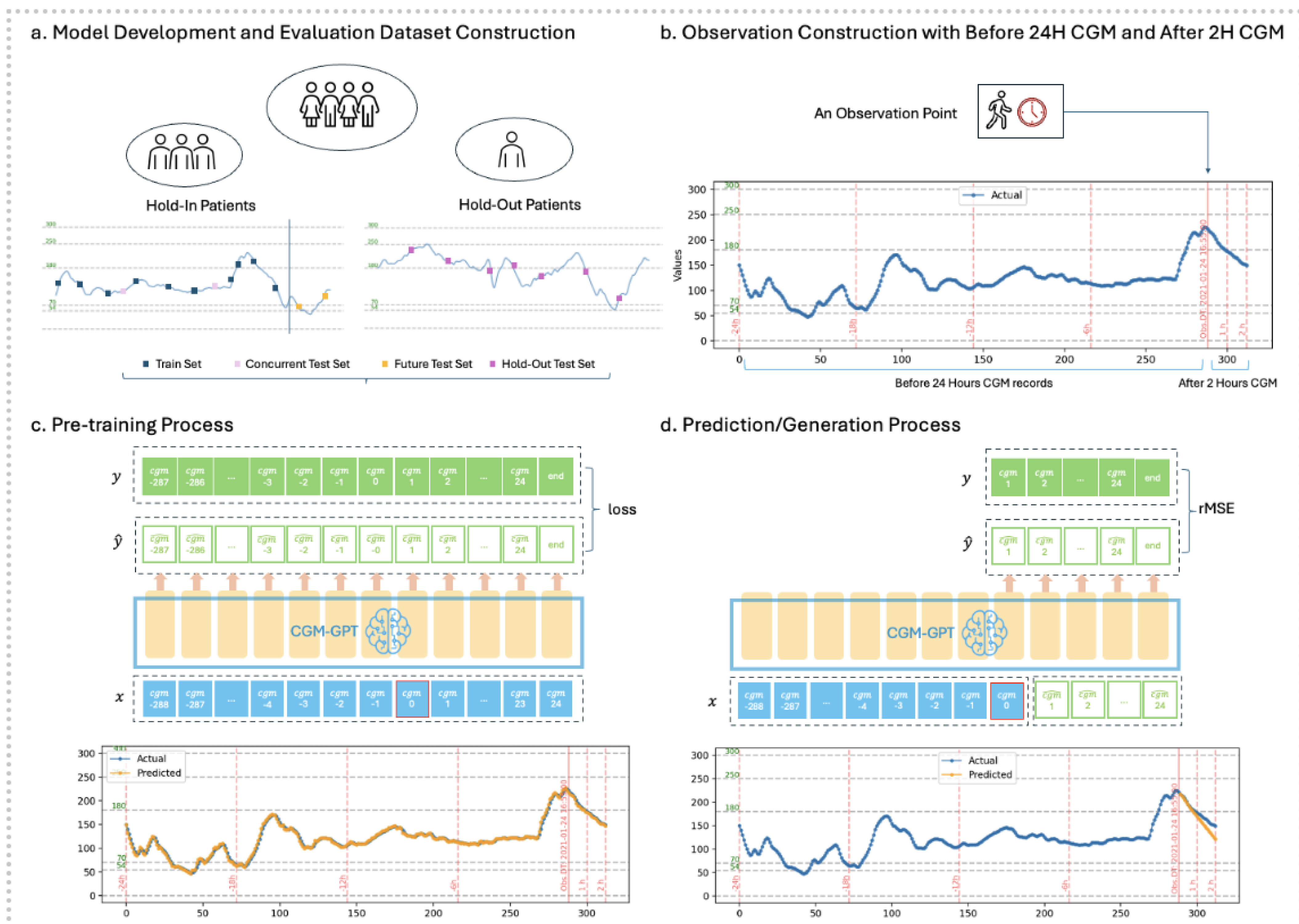
MATERIALS AND METHODS

We constructed two different GPT models: The first model, LSM-GPT, only used glucose data from both T1D and T2D populations in the training set to predict future glucose trajectories. The second model, LHM-GPT, used both glucose and food entry data from the same population to predict glucose trajectories at 30-minute, 60-minute, and 2-hour time horizons.

We evaluated real-world CGM from a digital health platform for 784 individuals with type 1 (T1D) and 1187 individuals with type 2 (T2D) diabetes for the LSM-GPT model. This dataset accounted for over 38 million CGM entries, covering approximately 134,770 patient-days (equivalent to 369 patient-years).

For the LHM-GPT model, we evaluated CGM and food data for 805 individuals with T1D and 1771 individuals with T2D. In total, there were 8,809 data points with each data point encompassing 24-hour CGM data and one food record. We used a 7:3 training to test split ratio. Model accuracy was evaluated by calculating the root mean square error (RMSE) (mg/dL) at each of these time intervals.

Figure 1: Model development workflow



RESULTS

For the LHM-GPT model— which included food and glucose data—the held-out sample RMSE for predicting T1D-only glucose trajectories at 30 minutes, 60 minutes, and 2-hours was 7.5, 15.0, and 25.9, respectively. The held-out sample RMSE for predicting T2D-only glucose trajectories at the same time intervals were 13.4, 22.1, and 31.8, respectively.

When comparing the LSM-GPT and LHM-GPT results, we observed no improvement in RMSE scores at the 30 minute interval. However, including food entries led to improved prediction accuracies at 60 minutes and 2-hour intervals for both populations. For T1D population, prediction accuracy improved by approximately 6% and 13% at 60 minutes and 2 hours, respectively. For the T2D population, accuracy improved by approximately 1% and 6% at the same time intervals.

Table 1: Prediction performance

RMSE = Root Mean Square Error (mg/dL)

Model Type (Input Data Type)	Population Type	RMSE - 30 min	RMSE - 60 min	RMSE - 120 min
LSM-GPT (Glucose Only)	Type 1 Diabetes	7.0	16.0	29.7
	Type 2 Diabetes	13.3	22.4	33.8
LHM-GPT (Food+Glucose)	Type 1 Diabetes	7.5	15.0	25.9
	Type 2 Diabetes	13.4	22.1	31.8

CONCLUSIONS

In this study, we show that combining glucose data with food covariates variables can improve the glucose prediction accuracy at 60 minutes and 2-hour time intervals in both T1D and T2D populations, with the T1D population showing greater accuracy improvements when compared to that of the T2D population. This suggests that food may play a larger role in influencing glucose levels in individuals with T1D than in those with T2D.
Our results also indicate that the improvement in prediction accuracy is greater for a 2-hour time horizon than 60-minute horizon. Since postprandial glucose typically peaks around 90 minutes[3], it is logical that including food as a covariate improves prediction accuracy at 2-hour interval, when the impact of food on glucose levels is at its highest. In the future, we may also want to study the impact of additional variables such as exercise and food intake behavior on glucose predictions from 2-hours to 8-hours.

This work not only establishes a pathway for assessing the value of integrating various health data into AI models but also underscores the importance of evaluating model accuracy over longer prediction periods. A key real-world application of this improved accuracy is the potential to help address challenging clinical issues, such as reliably predicting and preventing overnight hyperglycemia.

REFERENCES

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