CGM-GPT: A Transformer Based Glucose Prediction Model to Predict Glucose Trajectories at Different Time Horizons

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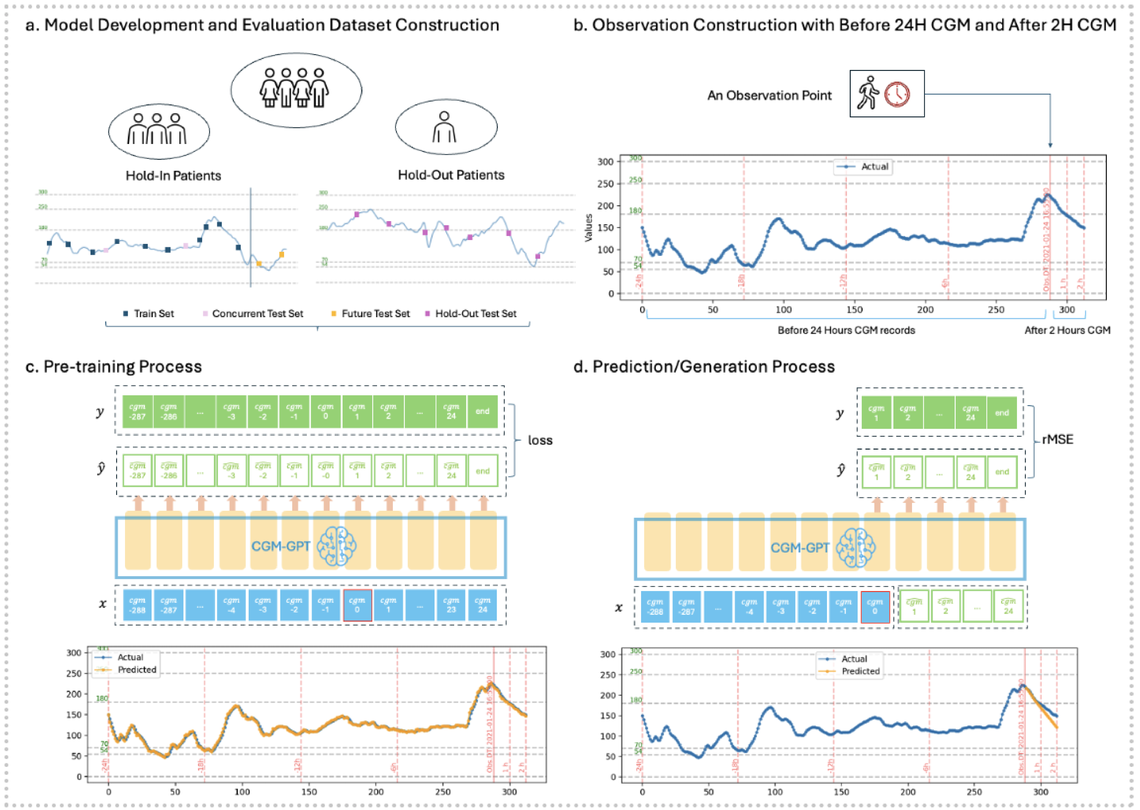
BACKGROUND AND AIMS

Accurate glucose value prediction and the subsequent, automated coaching based on these predictions are important to and can help improve the self-management of diabetes[1]. We have previously shown that by combining dense continuous glucose monitoring (CGM) sensor data with medication, education, diet, activity, and lab data (MEDAL) from a digital health solution, we can accurately predict binary outcome variables, such as whether the glucose time in range (TIR) will be above or below a certain threshold. In this study, we aimed to construct a Large Sensor Model (LSM) using a transformer architecture to predict the next glucose value, thereby providing glucose trajectories over 30 minutes, 60 minutes, and 2-hour intervals, which we refer to as CGM-GPT. Additionally, we compared the accuracy of our CGM-GPT models to that of other deep learning-based models reported in the current literature for the same time horizons in question.

MATERIALS AND METHODS

We evaluated real-world CGM data from a digital health platform for 617 individuals with type 1 (T1D) and type 2 (T2D) diabetes. This dataset accounted for over 17 million CGM entries, covering approximately 59,000 patient-days (equivalent to 161.7 patient-years). The dataset was down-sampled to 10%, and it was further split into a held-in sample and a held-out sample with a ratio of 9:1. We constructed two different GPT models: The first GPT model (GPT1) used only T1D population data in the training set, and the second GPT model (GPT2) used only data from the T2D population in the training set. Each of these models was used to predict glucose trajectories for both T1D and T2D populations at 30-minute, 60-minute, and 2-hour time horizons. Model accuracy was evaluated by calculating the root mean square (RMSE) (mg/dL) at these time intervals.

Figure 1: Model development workflow



RESULTS

For the GPT1 model, the held-out sample RMSE (mg/dL) for predicting T1D-only glucose trajectories at 30 minutes, 60 minutes, and 2-hours were 12.8, 23.5, and 40.1, respectively. Similarly, for the GPT2 model, the held-out sample RMSE for predicting T2D-only glucose trajectories at the same time intervals were 10.4, 17.5, and 27.4, respectively. Comparing our RMSE scores for the GPT1 model (used to predict T1D population glucose trajectories) to state-of-the art scores from the current literature, we found that our RMSE scores were considerably lower than for the state-of-the-art models [2,3,4], with the current literature average for the 30-minute and 60-minute RMSE scores being 18 and 30 mg/dL, respectively.

Table 1: Prediction performance

RMSE = Root Mean Square Error (mg/dL). Data shown is Mean (5% Confidence Interval)

Model	Dataset		RMSE-30min	RMSE-60min	RMSE-2Hr
Benchmark	OhioT1D		18.7 (2.60)	33.0 (3.6)	-
CGMGPT	OhioT1D *		9.4 (0.7)	15.6 (1.1)	26.3 (1.7)
	T1D (GPT1)	Concurrent Test	8.4 (0.1)	16.0 (0.1)	28.3 (0.2)
		Future Test	9.2 (0.1)	17.0 (0.1)	29.4 (0.2)
		Hold-Out Test	9.0 (0.1)	17.0 (0.1)	29.8 (0.2)
	T2D (GPT2)	Concurrent Test	7.4 (0.01)	13.4 (0.1)	22.6 (0.1)
		Future Test	8.0 (0.1)	14.1 (0.1)	23.2 (0.1)
		Hold-Out Test	7.8 (0.1)	14.0 (0.1)	23.4 (0.1)

* Prediction results using the GPT1 model applied to OhioT1D dataset

CONCLUSIONS

Novel transformer-based glucose prediction models can be highly accurate in predicting glucose trajectories at 30-minute, 60-minute and 2-hour time horizons for both T1D and T2D populations. Our GPT1 model achieved considerably lower RMSE scores when compared to those from current literature. Notably, none of the models in the current literature – based on deep learning architectures for glucose predictions – used the T2D population for training and predicting glucose trajectories at the specified time horizons. Additionally, our GPT1 and GPT2 models were the first to predict glucose trajectories at the 2-hour time horizons , which the state-of-the-art model did not do. In the future, we aim to enhance our GPT models by incorporating MEDAL data into the training sets and further investigating the breadth of applying the GPT2 model to predict glucose trajectories in a T1D population.

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