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Predicting Glucose Levels using Smartwatch Data

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Overview:



High glucose levels have negative long-term health effects.



Predicting adverse events such as high glucose levels can help people with prediabetes **protect their health**.



Dataset

Smartwatch





1. Cho, P., Kim, J., Bent, B., & Dunn, J. (2023). BIG IDEAs Lab Glycemic Variability and Wearable Device Data (version 1.1.2). PhysioNet. https://doi.org/10.13026/zthx-5212

2. Bent, B., Cho, P.J., Henriquez, M. et al. Engineering digital biomarkers of interstitial glucose from noninvasive smartwatches. npj Digit. Med. 4, 89 (2021). https://doi.org/10.1038/s41746-021-00465-w

Data Prep: Accelerometer





Data Augmentation: Glycemic Index (GI)

- GI quantifies how much a unit of carbohydrates in the given food raises the blood sugar.
- High GI means carbohydrates in that food are quickly absorbed → rapid rise in blood glucose.

Our dataset has a food log (e.g., "mashed potato", "chicken pot pie") → scrape and incorporate external GI database (University of Sydney)







Matching GI Data with LMs



We used SLM/LLM (Phi-3/GPT-4o) to match food description to the GI database:



High glucose events





Using carbohydrates to predict high glucose level



Glycemic index improves prediction





Predicting glucose levels over time

Inputs: Time-Dependent 10 Food data Heart rate **Output: Time Series Prediction** Our model 160 <u>₽₿₽</u> 000 Skin moisture 02-22 00 02-22 05 02-23 00 Glucose 32 -30 -28 -26 -24 -Temperature

3D Movement

Autoregressive Distributed Lag (ADL)

- ADL functions like an autoregressive (AR) model, but incorporates information from other time series into its predictions
- Our ADL model uses the smartwatch and food consumption data to predict a glucose reading
- Model was fit to each participant
- Hyperparameter optimization was used to find the best model for each participant
 - Hyperparameters optimized: Predictor set, Glucose lags, Predictor lags

ADL: GI Only



CV RMSE: 15.4 (mg/dL)



Participant 1, Glucose Lag 1, Predictor Lag 3

ADL: Smartwatch Only



CV RMSE: 15.5 (mg/dL)



Participant 1, Glucose Lag 1, Predictor Lag 3

ADL: GI + Smartwatch



CV RMSE: 14.6 (mg/dL)



Participant 1, Glucose Lag 1, Predictor Lag 3

Results

- Good fit for participants with reliably logged biometric data
- Participants with highly varying glucose data had worse fits
- Glycemic index was present in 8 of 13 best models

Participant #	Best Model RMSE Glucose Conc.(mg/dL)
1	14.19
2	19.09
3	19.39
4	18.75
5	10.62
6	22.76
8	16.54
9	22.87
10	23.20
11	19.98
12	16.34
14	20.75
16	16.82

Long Term Prediction



After training on 4 days of data, this model is capable of predicting the glucose readings for 5 days, given only smartwatch and food data for the same period.



Participant 5, Glucose Lag 1, Predictor Lag 6

Future Work

- Developing a mobile application that provides real-time alerts and personalized dietary recommendations.
- Improve data cleanup and alignment process.
- Incorporating additional data such as inter-beat interval.
- Investigating the feasibility of predicting the time to reach/recover from the peak glucose level after a meal.



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