LLM-Powered Prediction of Hyperglycemia and Discovery of Behavioral Treatment Pathways from Wearables and Diet

Sensors **2025**, *25*(17), 5372; https://doi.org/10.3390/s25175372

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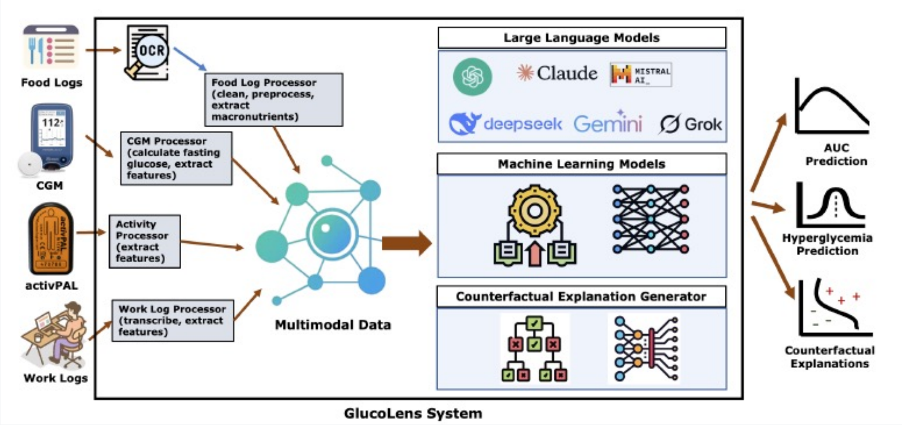

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Slides updated: 31 August 2025

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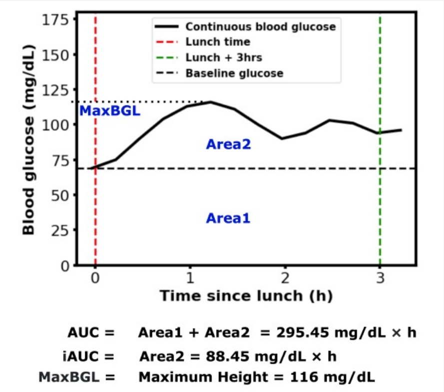

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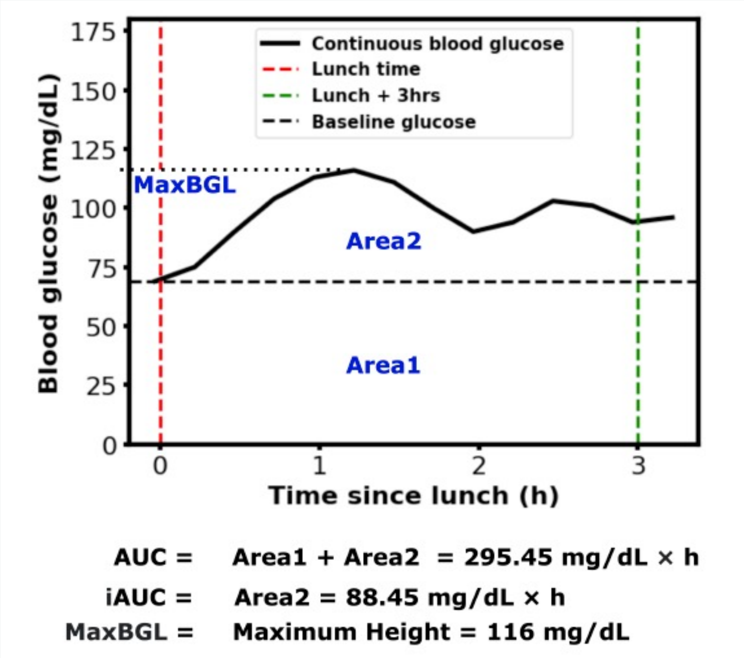
Introduction to Postprandial Hyperglycemia and Prediction

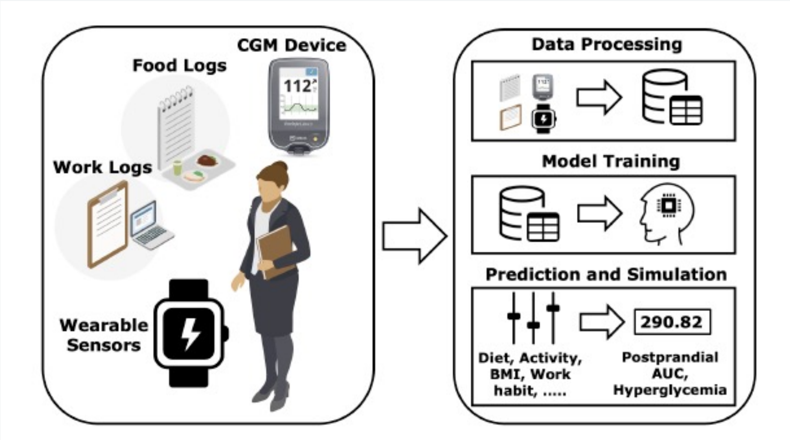
Significance of Postprandial Hyperglycemia

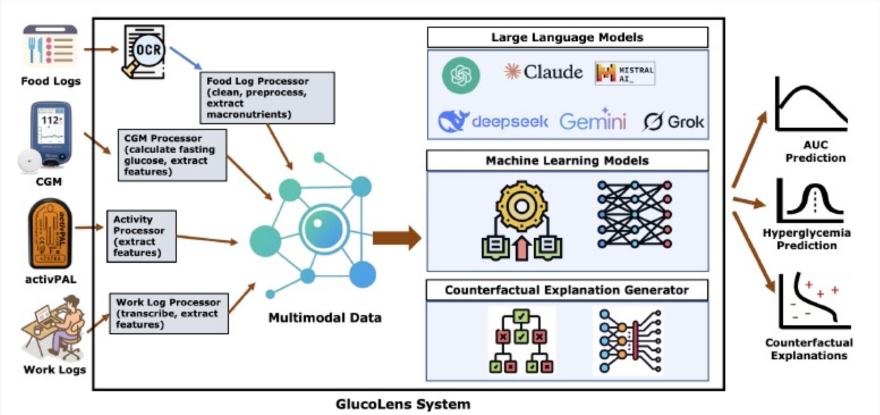
Postprandial hyperglycemia, defined by elevated blood glucose after meals, is a critical marker for progression toward type 2 diabetes. The postprandial area under the curve (AUC) is an important metric for blood glucose regulation and potential diabetes risk assessment.

Opportunity for Prediction and Intervention

By forecasting postprandial AUC in advance using lifestyle information such as diet and physical activity, individuals can proactively adjust their behaviors to maintain healthy glucose levels, potentially preventing the onset of diabetes.



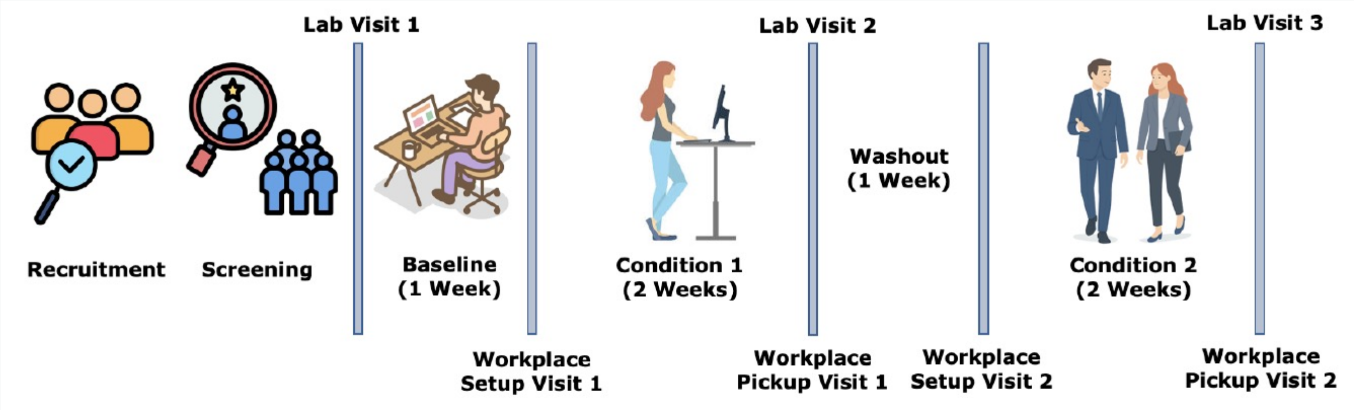




GlucoLens: An Explainable ML Solution

- GlucoLens is an explainable machine learning system designed to predict postprandial AUC and hyperglycemia.
- Integrates advanced data processing, LLMs, and trainable ML models.
- Inputs include continuous glucose monitoring (CGM), physical activity tracked by wearable devices, and detailed food and work logs.

Clinical Trial and Data Collection



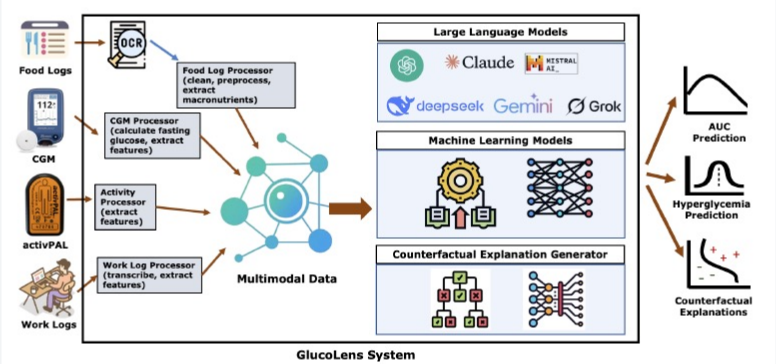
WorkWell Study Overview

- A five-week clinical trial, involved 10 full-time working adults.
- Data from CGM devices, activPAL, GENEActiv, food logs, and work logs
- Lunches were standardized and their nutritional contents precisely tracked.

Lifestyle and Activity Interventions

Participants underwent Baseline (usual habits), 'Stand' (maximal standing), and 'Move' (maximal movement) conditions in randomized order

(a) (b) (c)



No.	Feature Name/ Shorthand	Sensor +GL	Sensor +Macro	Self +GL	Self +Macro	All	Description
1	Fasting glucose	☒	☒	☒	☒	☒	Minimum CGM reading between 6 AM and 10 AM. (mg/dL).
2	Recent CGM	☒	☒	☒	☒	☒	Mean glucose concentration from 12 AM to 8 AM (mg/dL)
3	Lunch time	☒	☒	☒	☒	☒	Time when lunch was consumed (HH:MM).
4	Work from home	☒	☒	☒	☒	☒	Binary flag indicating work from home (0 or 1).
5	BMI	☒	☒	☒	☒	☒	Body Mass Index (kg/m^2).
6	Calories	☒	☒	☒	☒	☒	Total meal calories (kcal).
7	Calories from fat	☒	☒	☒	☒	☒	Caloric contribution from fat (kcal).
8	Saturated fat	☒	☒	☒	☒	☒	Saturated fat content of meal (g).
9	Trans fat	☒	☒	☒	☒	☒	Trans fat content of meal (g).
10	Cholesterol	☒	☒	☒	☒	☒	Cholesterol in the meal (mg).
11	Sodium	☒	☒	☒	☒	☒	Sodium intake from the meal (mg).
12	Total carbs	☒	☒	☒	☒	☒	Total carbohydrate amount (g).
13	Sugar	☒	☒	☒	☒	☒	Sugar content in the meal (g).
14	Work start time	☒	☒	☒	☒	☒	Time when the user started working (HH:MM).
15	Day of the week	☒	☒	☒	☒	☒	Categorical variable indicating weekday (Mon–Sun).
16	activPAL	☒	☒	☐	☐	☒	Sitting, standing, and stepping durations for the same day until the time of lunch as well as those durations at work for that day before lunch (seconds).
17	Self-reported activity	☐	☐	☒	☒	☒	Sitting, standing, and stepping durations manually reported (percentages of the work duration for each day).
18	GL	☒	☐	☒	☐	☒	Glycemic load of the meal (unitless index).
19	Net carbs	☐	☒	☐	☒	☒	Total carbs minus fiber (g).
20	Fat	☐	☒	☐	☒	☒	Total fat content in the meal (g).
21	Protein	☐	☒	☐	☒	☒	Protein content of the meal (g).
22	Fiber	☐	☒	☐	☒	☒	Dietary fiber amount in the meal (g).
23	AUC	☐	☐	☐	☐	☐	Outcome variable. 3-h postprandial area under the curve (mg/dL · h). In this study, we used the absolute AUC value without normalizing.

Feature Engineering and Data Processing

1 Multimodal Data Processing

- Handwritten food and work logs were digitized using OCR and manual intervention.
- Features were engineered from dietary macronutrients, glycemic load calculations, wearable-derived activity metrics, and work habits.
- CGM data were processed for fasting and recent glucose metrics.

2 Comprehensive Feature Sets

Five different feature sets were formed, integrating self-reported and sensor-based activity data, macronutrients, glycemic load, and daily routines, yielding 31 features for model input including both objective and self-reported lifestyle information.

Machine Learning Architectures and Modeling Approaches

Backbone Model Experiments

GlucoLens utilized multiple ML model backbones, including Random Forests (RF), Ridge Regression, Multilayer Perceptrons (MLP), XGBoost, and TabNet. Extensive hyperparameter tuning was performed, including variation in model depth, regularization, and ensemble combinations.

Integration with Large Language Models (LLMs)

Zero-shot LLMs (e.g., GPT-4, Claude Opus 4) were employed for predictions and as hybrid inputs to ML models. LLM-only, hybrid, and base models were systematically compared for performance and interpretability.

Target outcomes	AUC, MaxBGL, Hyperglycemia
Feature sets	Sensor + Macro, Self + Macro, Sensor + GL, Self + GL, All
Predictors	RF, Ridge, MLP, XGBoost, TabNet, GPT-3.5, GPT-4, Mistral Large, Gemini Flash 2.0, Claude Opus 4, Grok 3, Deepseek V3, Gly_Hybrid, Gly_Hybrid_v2, Gly_Max, Hybrid Predictors for Classification (RF+MLP, RF+XGB, XGB+MLP, RF+XGB+MLP).
Ridge variations	$\alpha \in \{1, 0.1, 0.01\}$
RF variations	$n_{est} \in \{10, 50, 100\}$
MLP variations	13 variations; see Table 3

Prompt

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Instruction:
The goal is to predict the 3-hour postprandial AUC (area under the CGM curve from lunch to 3 hours after
lunch, not the incremental AUC) based on the following features:

['fasting_glucose', 'recent_cgm', 'lunch_time', 'work_at_home', 'recent_activity', 'bmi', 'Calories',
'Calories From Fat', 'Total Fat (g)', 'Saturated Fat (g)', 'Trans Fat (g)', 'Cholesterol (mg)', 'Sodium
(mg)', 'Total Carbs (g)', 'Fiber (g)', 'Sugars (g)', 'Net Carbs(g)', 'Protein (g)', 'is_Friday',
'is_Monday', 'is_Thursday', 'is_Tuesday', 'is_Wednesday', 'sitting_total', 'standing_total',
'stepping_total', 'sitting_at_work', 'standing_at_work', 'stepping_at_work', 'work_start_time',
'glycemic_load'].

fasting_glucose and recent_cgm are given in mg/dL. lunch_time and work_start_time are represented as
hour values (e.g., 7.75 means 7:45 AM, 13.50 means 1:30 PM). recent_activity score is calculated by
taking the average percentage of time spent in walking activity in the previous days of the same phase
and adding 0.5 times the average percentage of time spent in standing activity in the previous days of
the same phase. sitting, standing, and stepping features are in seconds for the specific day before
lunch.

Task:
Predict the 3-hour postprandial AUC for the given features.
Give me just the number enclosed within the <Prediction></Prediction> tags.

Input:

[48.0, 58.0625, 12.25, 1.0, 10.0, 36.7, 350.0, 100.0, 12.0, 2.0, 0.0, 45.0, 220.0, 27.3, 5.0, 3.0, 22.3,
32.3, 0.0, 0.0, 0.0, 0.0, 1.0, 17363.8, 1393.7, 380.1, 16843.6, 132.2, 124.2, 7.5, 14.7641].

Output:
```

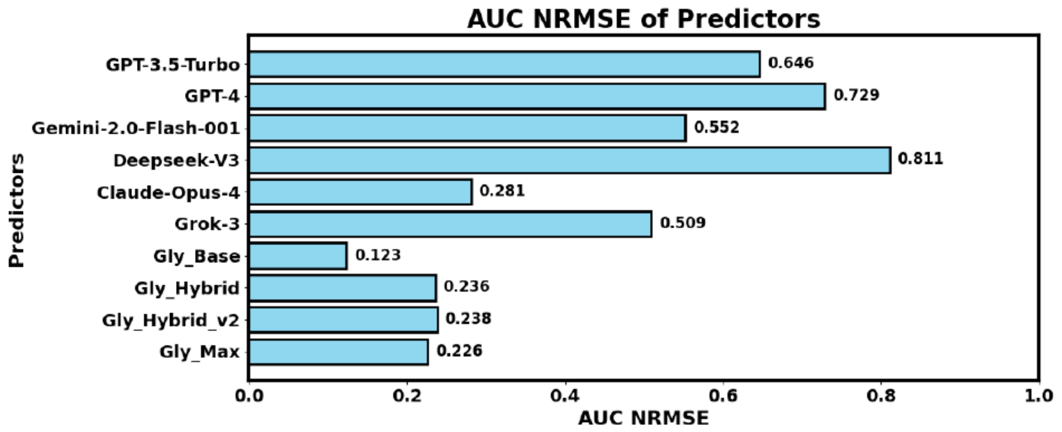
Results: AUC Prediction Performance

Table 4. Normalized Root Mean Squared Errors (NRMSEs) of our GlucoLens models (RF, Ridge, MLP, XGBoost, TabNet) for different feature sets in the prediction of postprandial AUC. Explanations of the feature sets can be found in Table 1. Boldfaced values represent the best results for the corresponding feature sets.

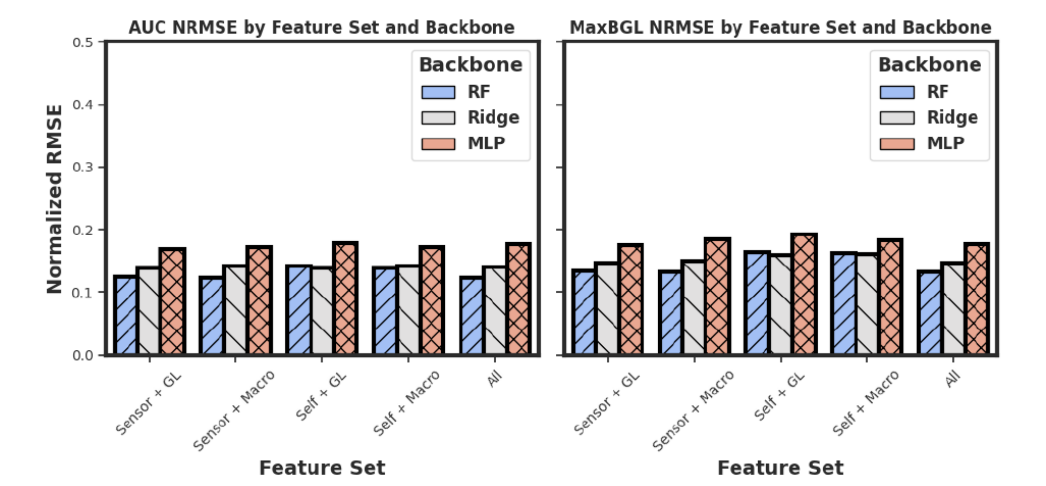
Feature Set	RF	Ridge	MLP	XGBoost	TabNet
Sensor + GL	**0.125**	0.139	0.169	0.137	0.160
Sensor + Macro	**0.123**	0.142	0.172	0.139	0.147
Self + GL	0.142	**0.139**	0.178	0.152	0.154
Self + Macro	**0.139**	0.142	0.172	0.149	0.151
All	**0.123**	0.140	0.176	0.137	0.151

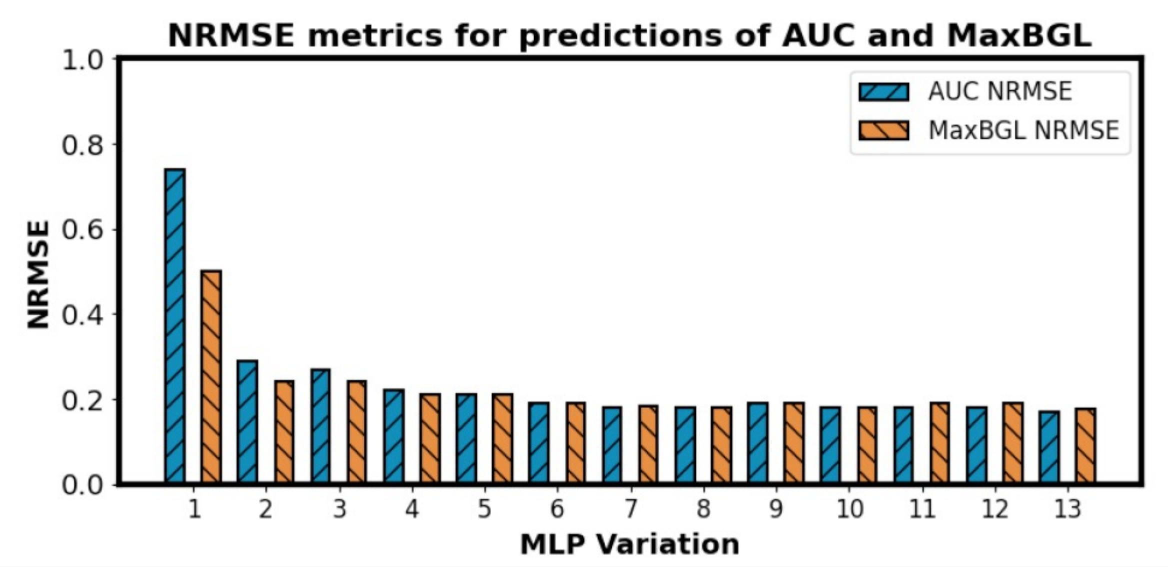
Table 5. AUC NRMSE results of different variations in our solution. Gly_Base = GlucoLens regressor with no LLM, Gly_LLM = LLM only prediction (zero-shot) after multimodal data processing by GlucoLens. The hybrid predictors are explained in Table 2. The best result is bolded.

Backbone	Gly_Base	Gly_LLM	Gly_Hybrid	Gly_Hybrid_v2	Gly_Max
RF	**0.123**	0.281	0.241	0.238	0.226
XGBoost	0.137		0.236	0.242	0.259



Results: MaxBGL and MLP performances





Hyperglycemia Detection Models

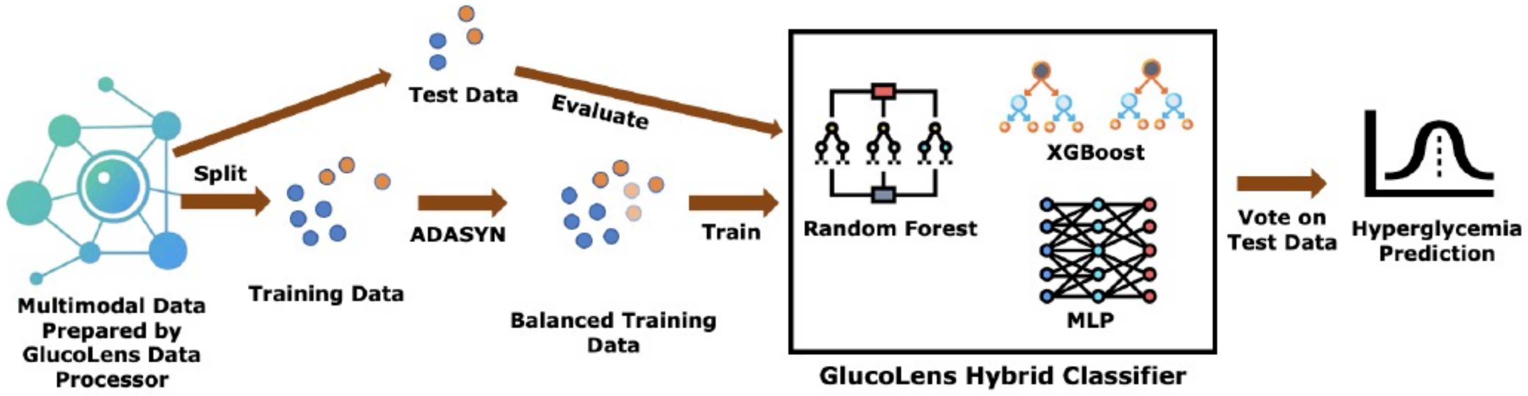


Figure 6. The pipeline of classification of hyperglycemia with GlucoLens system's hybrid classifier. A soft voting based on the probabilities of classes suggested by the RF, XGBoost, and MLP (version 13 of Table 3) is used to make the final predictions. This hybrid method outperforms the prediction performances of single classifiers. The test set contains only real datapoints, so that the evaluation is not biased by the data generation method, whereas the balanced training data contains both real and synthetic datapoints.

Hyperglycemia Detection Results

Table 6. GlucoLens system's classification results with different pure and hybrid backbones for hyperglycemia detection on the 87% training and 13% test split. All metrics are averages over 100 repetitions with different random seeds. Best results and the best configuration are bolded.

Classifier	Accuracy	Precision	Recall	F1
RF	0.698	0.737	0.699	0.685
XGB	0.685	0.720	0.692	0.682
MLP	0.620	0.626	0.620	0.589
RF+XGB	0.695	0.730	0.695	0.683
RF+MLP	0.668	0.700	0.668	0.650
XGB+MLP	0.687	0.712	0.687	0.672
RF+XGB+MLP	**0.712**	**0.740**	**0.712**	**0.702**

Table 7. Results of the GlucoLens hyperglycemia detection system with RF+XGB+MLP-based hybrid backbone as we increase the training data size. All metrics are averages over 100 repetitions with different random seeds. An improvement in the performance metrics can be observed except for the last row, when only 1% of the dataset is withheld for testing. In that case, the evaluation in any trial is vulnerable to producing 0 values for precision, recall, or F1 score, as there is only 1 example from each class in the test set. Eventually, it affects the overall average of those metrics. Best results and the best configuration are bolded.

Size of Training Set	Accuracy	Precision	Recall	F1
70% training, 30% test	0.674	0.706	0.674	0.660
80% training, 20% test	0.660	0.729	0.702	0.690
87% training, 13% test	0.712	0.740	0.712	0.702
90% training, 10% test	0.717	0.744	0.717	0.705
95% training, 5% test	**0.733**	**0.751**	**0.733**	**0.716**
99% training, 1% test	0.730	0.625	0.730	0.660

Hyperglycemia Detection Results (contd.)

Table 8. Comparison of hyperglycemia prediction performance of RF+XGB+MLP hybrid classifier with and without data augmentation. A 10-fold cross-validation was used for classification. No balancing or augmentation was performed on the test set in either case. Best average results are bolded.

	Accuracy	Precision	Recall	F1 Score
Without Augmentation				
Trial 1	0.786	0.749	0.749	0.749
Trial 2	0.755	0.714	0.721	0.717
Trial 3	0.748	0.705	0.705	0.705
Average	0.763	0.723	0.725	0.724
With Augmentation				
Trial 1	0.774	0.735	0.723	0.728
Trial 2	0.786	0.749	0.749	0.749
Trial 3	0.811	0.783	0.762	0.771
Average	**0.790**	**0.756**	**0.745**	**0.749**

Counterfactual Explanations

Orignal exmple: Hyperglycemia

Current feature values:
Fiber: 1 g
Stepping duration: 8.95 minutes

Counterfactual examples: Normal blood glucose level

Option 1: Increase fiber intake to 5 grams ↑.

Option 2: Increase stepping duration to 39.38 minutes ↑.

Orignal exmple: Normal blood glucose level

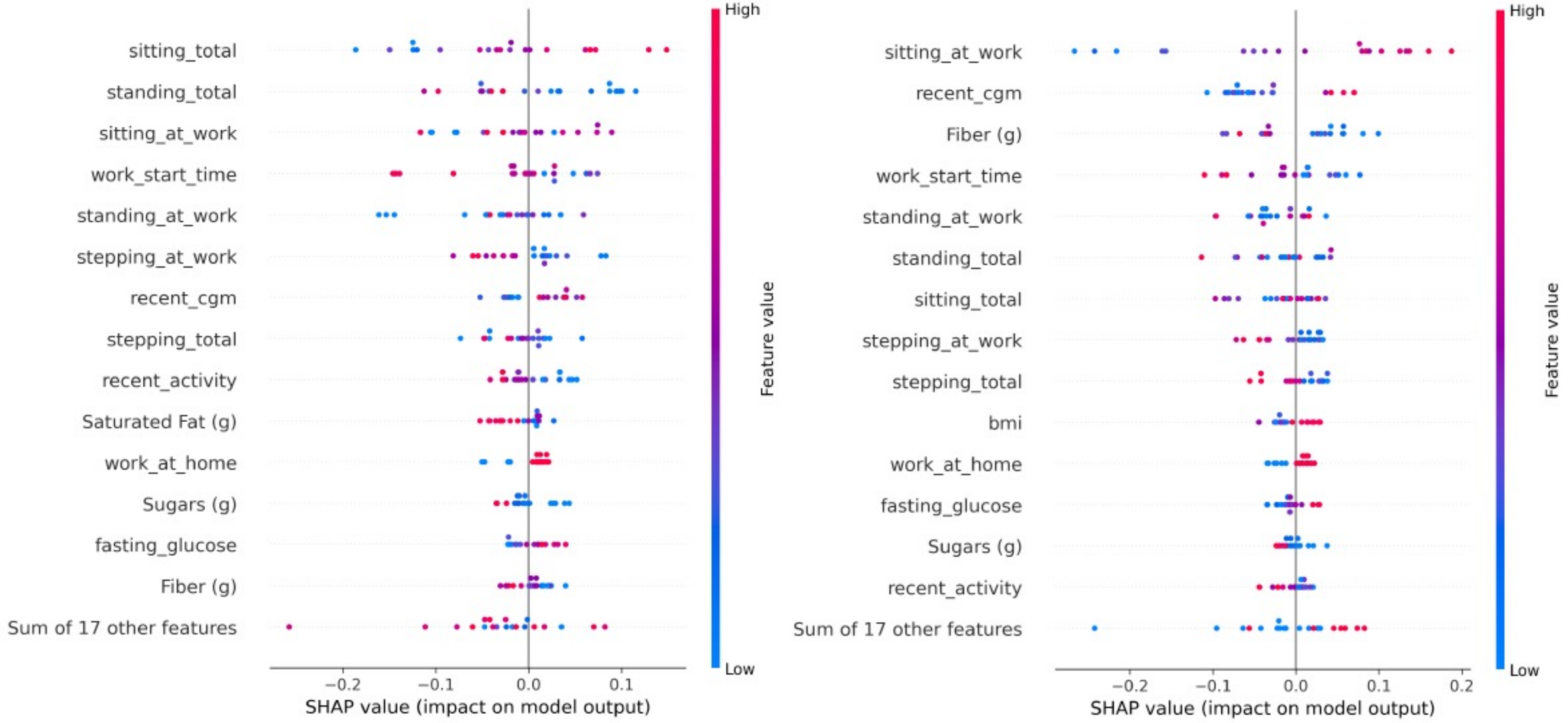
Current features values:
Work start time: 11 AM
Sitting at work: 48.31 minutes
Lunch time: 1 PM
Calories in lunch: 780 kCal

Counterfactual examples: Hyperglycemia

Option 1: Start working at 6 AM ↓, increase sitting duration at work to 148.62 minutes ↑, eat lunch at 12 PM ↓, increase lunch calories to 827 kCal ↑.

Metric	Value
Average validity	1.000
Average diversity	3.945
Average normalized distance	2.258
Average features changed	2.000

SHAP Explanations



(a) SHAP plot for hyperglycemia

(b) Another SHAP plot for hyperglycemia

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