MealMeter: Using Multimodal Sensing and Machine Learning for Automatically Estimating Nutrition Intake

Asiful Arefeen, Samantha Fessler, Sayyed Mostafa Mostafavi, Carol S Johnston, and Hassan Ghasemzadeh

Embedded Machine Intelligence Lab (EMIL), College of Health Solutions, Arizona State University, USA

SCAN ME

asiful-arefeen.com

SCAN ME

github repository

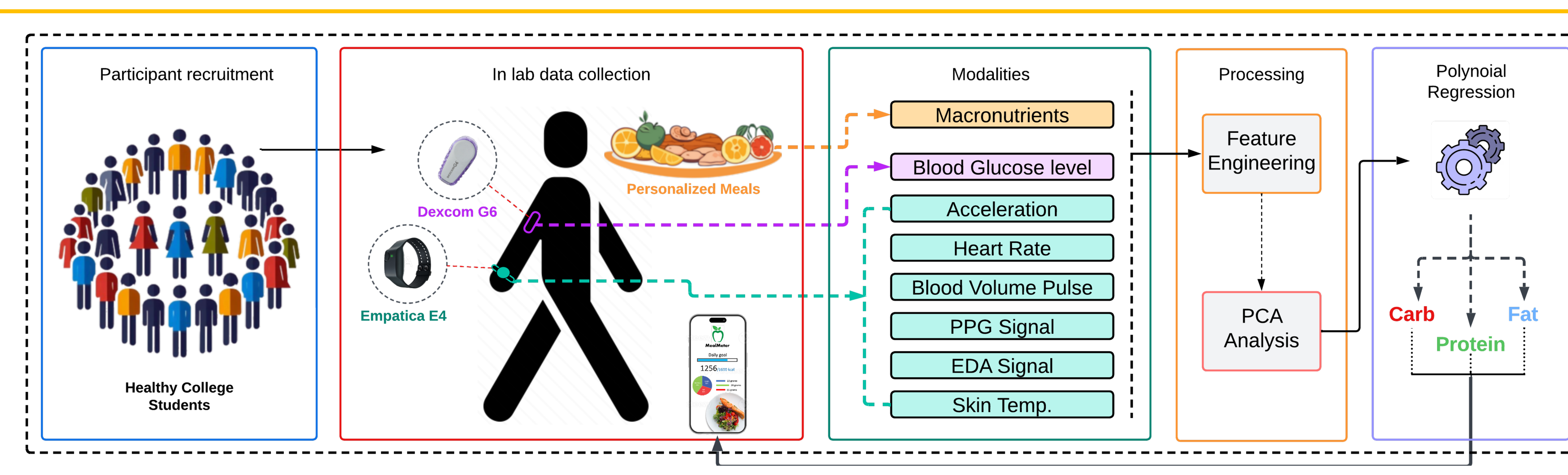
INTRODUCTION

Meal content tracking is a prerequisite for precision nutrition and metabolic health monitoring. Self-reported food logs or dietary recalls are prone to inaccuracies and biases. We propose ***MealMeter***, a lightweight machine learning-driven method that leverages multimodal sensor data from wearable and mobile devices to track meal contents. Data are collected from 12 participants in controlled condition. We integrate physiological signals (continuous glucose, heart rate variability), and inertial motion data to model the relationship between meal intake and metabolic responses.

MealMeter significantly improves meal macronutrient estimation compared to the baselines, achieving average mean absolute errors (MAE) and average root mean squared relative errors (RMSRE) of 13.2 grams and 0.37, respectively, for carbohydrates.

AIMS

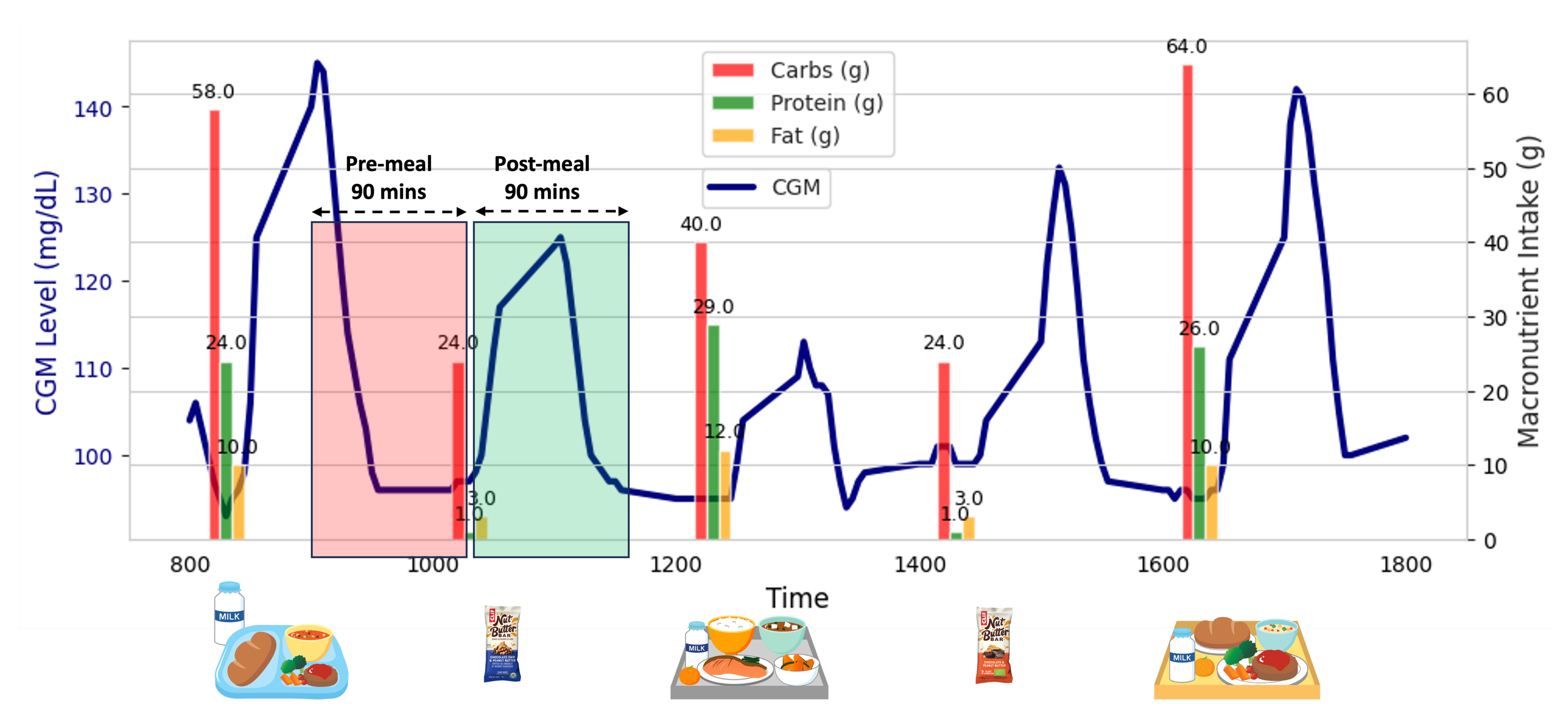
1. Develop a unique dataset from 12 healthy individuals equipped with CGM sensor and Empatica E4 to capture metabolic response to customized meals for three non-consecutive days
2. Use the data from the user study to train lightweight regression models to map meal macronutrients from physiological signals and explore associations among these parameters



Pipeline: MealMeter performs multimodal fusion using data from Dexcom G6 CGM and Empatica E4 followed by feature engineering and light-weight model training for dietary assessment

DATASET

- **Participants:** 12 healthy adults (ages 23–31, BMI 20.08–31.84)
- **Devices:** **Dexcom G6 CGM** to capture blood glucose every 5 minutes, **Empatica E4 wristband** to record Acc, EDA, HR, BVP, and skin temperature (4Hz to 64Hz)
- **Study time:** 3 non-consecutive days, with 10 hours of monitoring each day in controlled setting
- **Custom meals:** Each day was one of Hypercaloric, Eucaloric or Hypocaloric, customized to resting energy expenditure and served at 8:30, 12:30, 16:30, with snacks at 10:30 AM and 14:30
- **Limited mobility:** Participants remained sedentary and were prompted every 30 minute through smartphone about their activity



CGM signal as response to the food items fed at different timestamps. 90-minute long pre- and post-meal windows are two of many inputs to the pipeline

Method

1. Resample all signals to 8 Hz. Use moving average filter to reduce noise, smoothen high-frequency and preserve underlying trends.
2. Cropped 90-minute pre-meal glucose level and 90-minute post meal glucose level, Acc, EDA, HR, BVP, and skin temperature from each meal event.
3. Feature engineering:

Time-Domain	Frequency-Domain
Min, Max, Skewness, Mean, SD, Kurtosis, Range, Root Mean Square (RMS), Median, Autocorrelation, Interquartile Range (IQR), Entropy, Zero-Crossing Rate (ZCR)	Power Spectral Density, Dominant Frequency, Spectral Entropy

4. Features were standardized using z-score normalization and went through Principal Component Analysis (PCA)

$$X_{scaled} = \frac{X - \mu}{\sigma} \qquad Z = X_{scaled} W$$

5. Train a linear regression model for meal macronutrient estimation and estimate signal contributions

$$y = \beta_0 + \sum_i \beta_i z_k + \epsilon$$

Results

Subject specific performance

1. For carbohydrate intake, MAE values were from 3.96 g to 32.38 g, with an average of 17.64 g.
2. MAE for fat estimation was between 1.03 g and 11.35 g, with an average of 4.75 g. 4.6, with an average of 0.86.

Subject agnostic performance

MealMeter outperformed the baselines with better MAE, RMSRE and Pearson R

Baselines

1. Huo et al.- 5 Gaussian kernels → captured the trend of glycemic response → fed it to a multi-task model

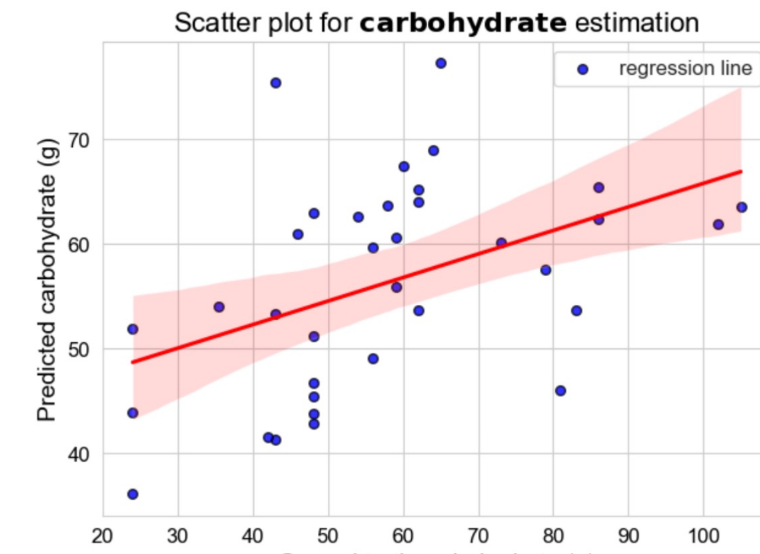
2. Yang et al. – Contrastive loss function → Siamese neural network (SNN) →Predict macronutrients

3. TabPFN - Transformer based foundation model for classification and regression on tabular data

TABLE II: MAE (grams) and RMSRE of estimated carbohydrate, protein and fat amounts for different subjects.

	Carbohydrate		Protein		Fat	
Subject	**MAE**	**RMSRE**	**MAE**	**RMSRE**	**MAE**	**RMSRE**
P1	24.12	0.28	7.55	0.37	1.03	0.09
P2	18.57	0.88	11.77	5.96	3.36	1.03
P3	10.54	0.2	18.45	8.54	2.77	0.53
P4	27.34	0.68	13.59	7.37	6.87	1.08
P5	3.96	0.08	7.51	0.37	3.59	0.25
P6	6.58	0.17	12.16	4.2	2.87	0.32
P7	19.21	0.26	14.08	0.44	5.48	0.32
P8	10.92	0.19	14.5	6.36	5.12	0.6
P9	31.94	0.38	16.97	7.66	11.35	0.66
P10	32.38	0.84	13.81	1.91	7.1	4.6
P11	15.65	0.34	2.93	2.21	3.79	0.6
P12	10.5	0.19	13.49	0.5	3.71	0.27
average	17.64	0.37	12.23	3.82	4.75	0.86

Scatter plot for **carbohydrate** estimation



Individual signal contributions for **carb** estimation

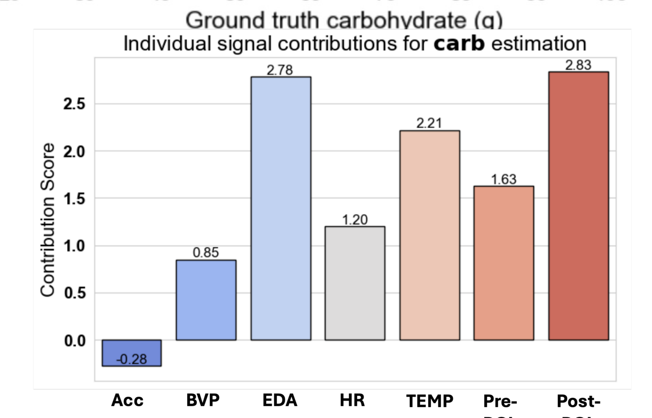


TABLE III: Comparing MealMeter against the baselines using MAE (grams), RMSRE and Pearson correlation

	Carbohydrate			Protein			Fat		
Method	**MAE ↓**	**RMSRE ↓**	***r* ↑**	**MAE ↓**	**RMSRE ↓**	***r* ↑**	**MAE ↓**	**RMSRE ↓**	***r* ↑**
MealMeter	**13.2**	**0.37**	**0.44**	**9.66**	4.51	**0.43**	**3.67**	0.74	**0.49**
Huo et al. [17]	14.8	0.5	0.36	12.8	5.2	0.2	4.8	0.82	0.29
Yang et al. [24]	17	0.51	0.42	10.5	7.2	0.42	4.7	1.02	0.41
TabPFN [25]	**13.2**	0.44	0.12	9.87	**3.61**	0.1	3.91	**0.63**	0.06

This work was supported in part by the National Institute of Diabetes and Digestive and Kidney Diseases of the National Institutes of Health under Award Number **T32DK137525**. 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 organization.

EMBEDDED MACHINE INTELLIGENCE LAB

College of Health Solutions
Arizona State University