AI-Driven Non-Invasive Blood Glucose Forecasting Using Multimodal Physiological Signals and Dietary Data

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Motivation & Objective

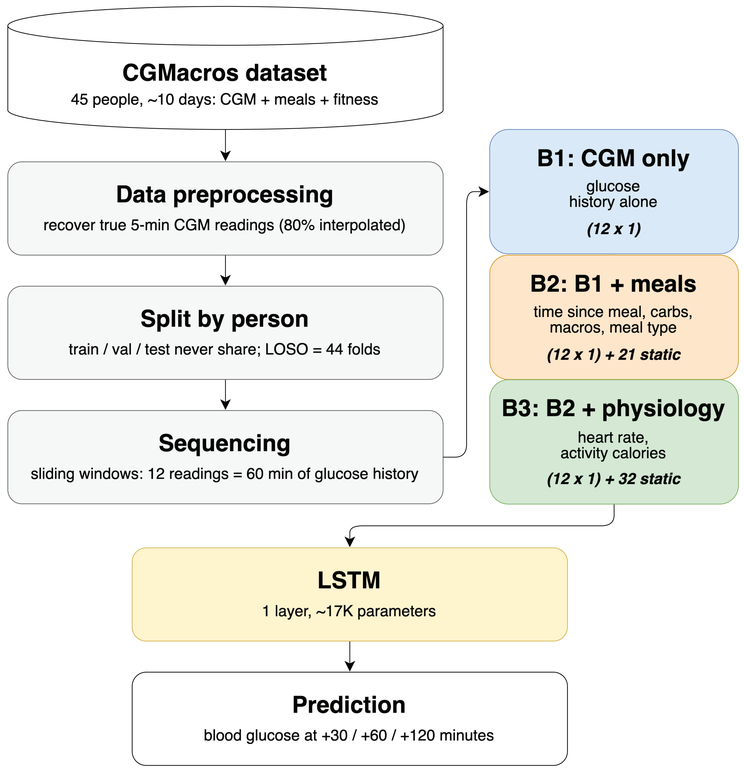
Accurate forecasting of future blood glucose can provide early warning of clinically relevant glucose changes.

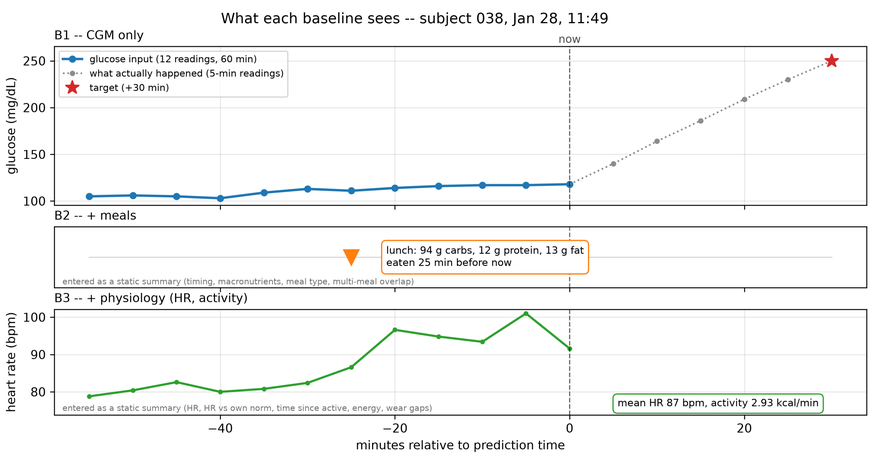
Glucose-only forecasting may miss changes associated with food intake and physiological activity.

This study investigates whether incorporating dietary and multimodal physiological information improves deep-learning-based glucose forecasts.

LSTM models are evaluated for forecasting horizons of 30–120 min using CGMacros.

Design Flow





Models Tested

Architectures: 1-layer, 2-layer, bidirectional, and attention LSTMs.

Result: all perform within 0.1 mg/dL – less than random-seed variation.

Selected: 1-layer LSTM, 17K parameters; simplest with equivalent performance.

Training: 11 random seeds, Adam optimizer, early stopping, fully deterministic.

Results

Post-meal forecast skill: 9.1% → 22.5% (more than doubles).
Dietary information substantially improves forecasting; best gains after meals.

Model	Split	RMSE (mg/dL)	NRMSE
Persistence	pooled	19.19 ± 1.33	0.053
B1, LSTM	pooled	17.69 ± 1.52	0.049
B1, LSTM (2-layer)	val sweep	within 0.04 of 1-layer	n/a
B1, BiLSTM	pooled	17.72 ± 1.28	0.049
B1, Attention LSTM	pooled	17.64 ± 1.39	0.049
B2, LSTM	pooled	**16.85 ± 1.17**	**0.047**
B3, LSTM	pooled	16.86 ± 1.19	0.047
Persistence	LOSO	20.12 ± 4.58	0.056
B1, LSTM	LOSO	18.42 ± 4.26	0.051
B2, LSTM	LOSO	**17.53 ± 3.83**	**0.049**

Showing forecasts evaluated at 30 minutes ahead for comparison

NRMSE = RMSE / 360 mg/dL (40–400 mg/dL sensor range)
Pooled rows average 11 training runs with different random seeds
LOSO rows average 44 folds, one per held-out subject
The 2-layer LSTM was compared during tuning on validation data

Key Results

Dietary info helps: B2 beats B1 in 11/11 seeds and physiology adds nothing.

Results hold on unseen subjects: 12.5% below persistence, 43/44 improve.

Clinically safer: 97% predictions in Parkes Zone A vs 93.5% for persistence.

Better inputs > fancier models: 4 architectures & hyperparameter sweep all tie.

Prediction Uncertainty

True glucose values fall within predicted intervals approximately 90% of the time, including for unseen subjects.

Prediction intervals widen appropriately during rapidly changing glucose conditions: approximately 24 mg/dL when stable versus 49 mg/dL when rising.

Takeaways

Forecasting gives 30–60 min of early warning, 97% clinically harmless.

Meals double forecast skill after eating; diabetic patients benefit most.

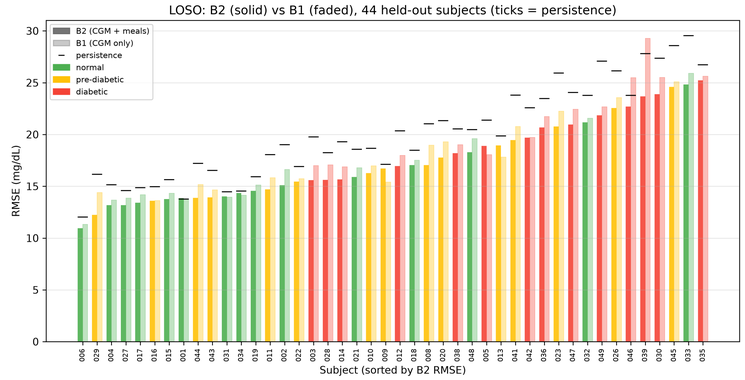
When you ate matters more than what you ate (macros not significant).

Among macronutrients, only carbohydrates add signal.

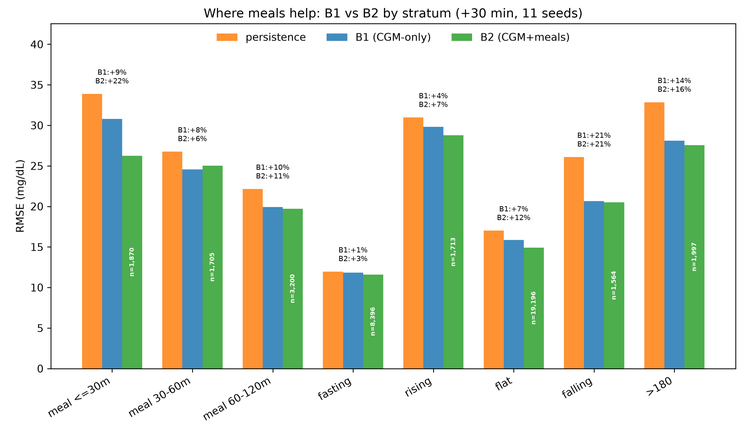
Activity added nothing, a puzzle that may need insulin data to solve.

What Drives Better Forecasts?

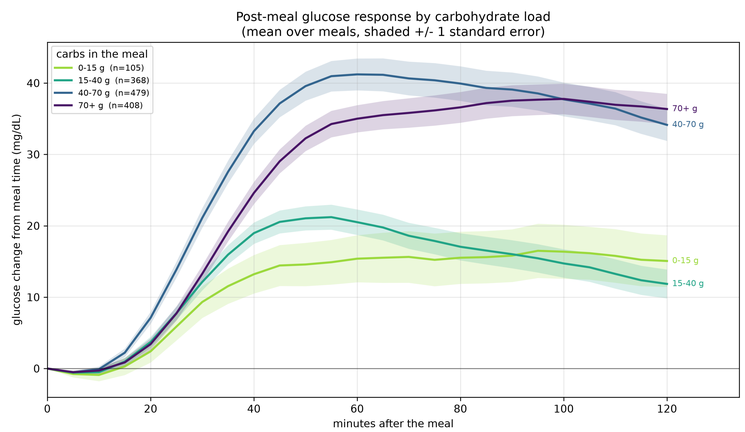
Dietary information, particularly meal timing and carbohydrate intake, provides the strongest signal, while activity information adds little benefit.



43/44 improve with meals; 039, 046 flip from below to above persistence



Most B2 improvements occur right after meals: 9.1% → 22.5% in skill



Larger carb loads drive bigger rises, saturating around ~40g