Predictive Modeling of Exercise-Induced Glycemic Outcomes Using Generative Deep Learning

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Motivation

- **Physiological models do not fully capture the complexity** of glucose homeostasis**.**
- Data-driven models learn from real-life data, including lifestyle factors

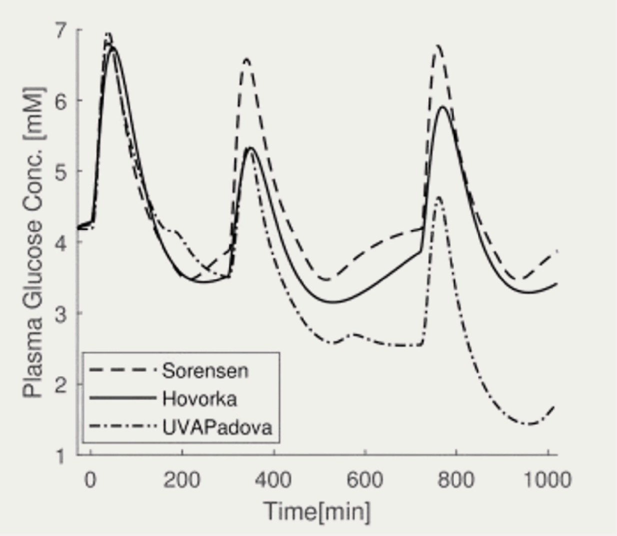

Figure 1: Blood glucose simulations using the three common physiological models [1].

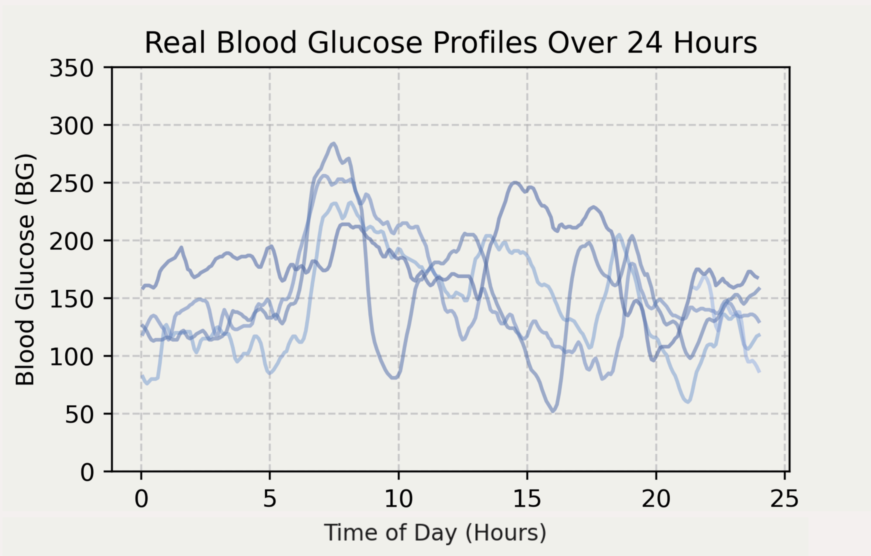

Figure 2: Overlay of multiple real 24-hour blood glucose profiles from T1DEXI.

Data-driven virtual patients

- Generative Adversarial Networks (GANs) can capture the complex and unpredictable **stochasticity** seen in real patients.
- Previous implementations focused on modeling patient responses to insulin and meals using GANs [2].
- **Objective**: Extend our simulator to incorporate **exercise activities**, aiming to replicate the behavioral patterns and long-term glycemic outcomes.

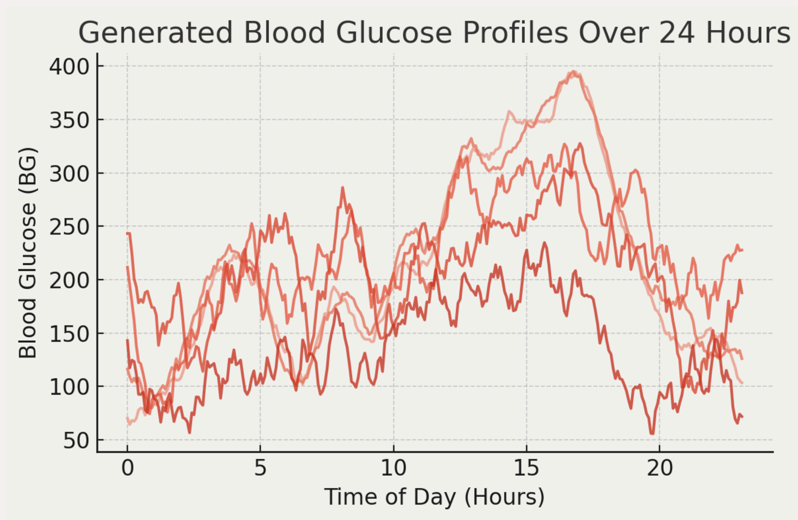

Figure 3: Overlay of multiple generated 24-hour blood glucose profiles: Demonstrating simulator stochasticity under identical inputs from [2].

Methods

- Implementation of a Wasserstein Conditional GAN.
- Produces shifted sequences with 120 min. prediction horizon.
- **Inputs**: estimated active: insulin, carbohydrates and exercise.
- **Data**: 60 standard insulin pump patients from **T1DEXI** dataset who were assigned **aerobic exercise.**
- Physical activity modeled via differential equation, with amplitude and temporal tau dependant on intensity.

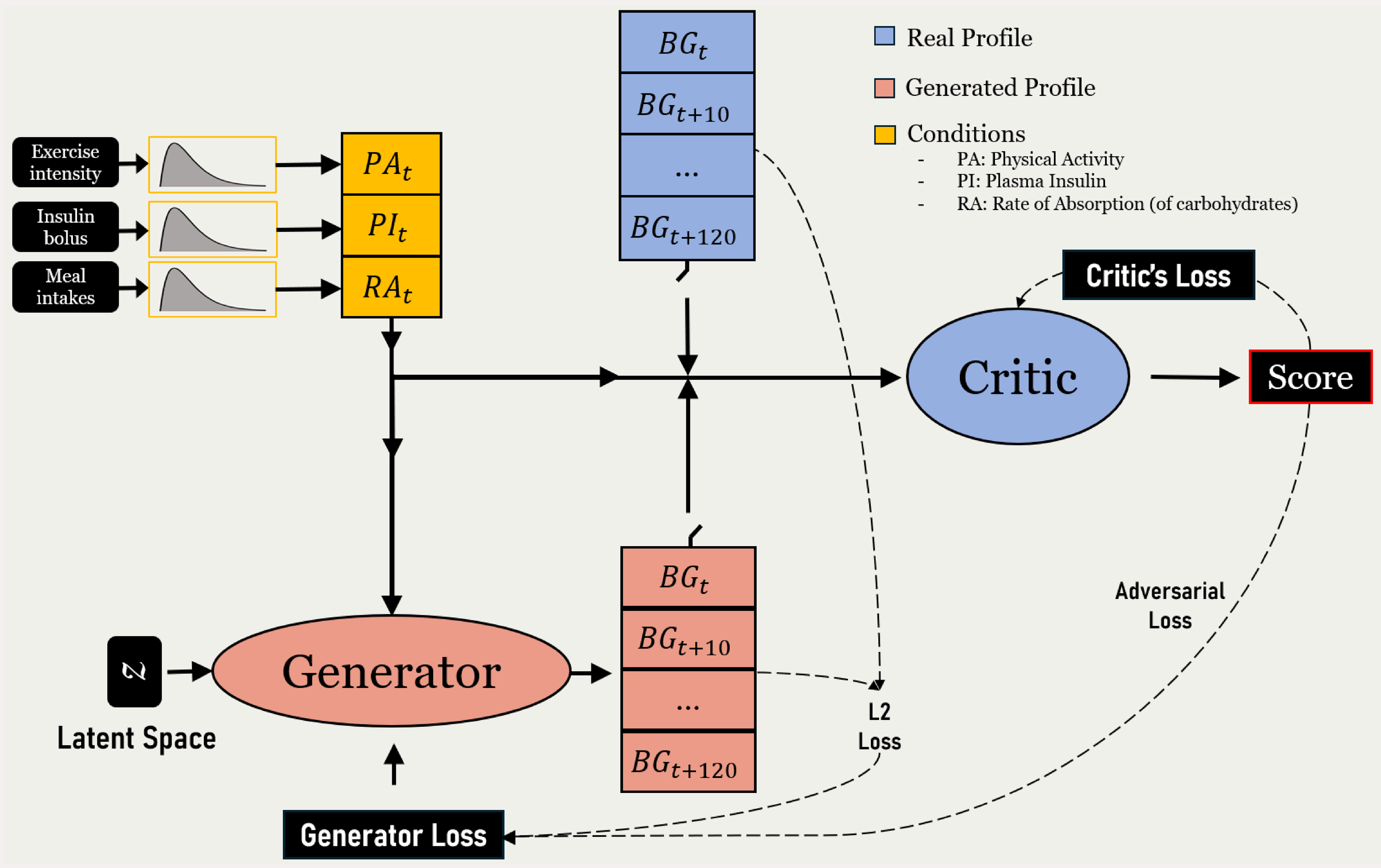

Figure 4: GAN architecture for training.

Results

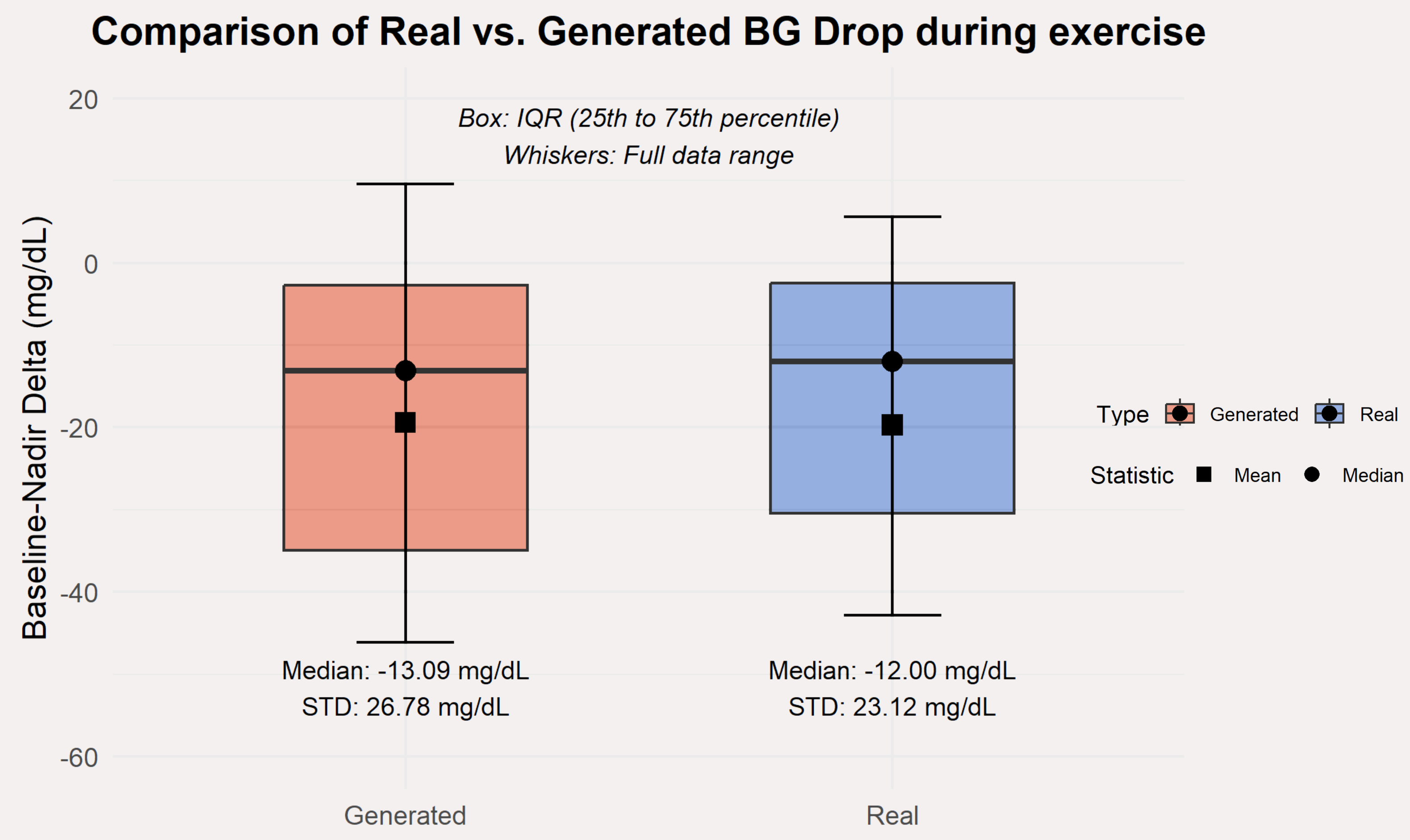

Figure 5: Boxplot of the drop in blood glucose concentration during exercise activity from baseline to nadir (minima during the activity).

Generated Real

Type		Mean Glucose	Std Glucose	Coef. Variation	Time < 70 (%)	Time in Range (%)	Time > 180 (%)	T. in Tight Range (%)
Sedentary	Generated	149.33	49.57	32.70	0.00	77.43	21.18	51.22
	Real	141.46	41.18	29.95	2.78	77.26	18.40	54.17
Active	Generated	145.60	40.75	31.00	1.39	79.17	20.14	48.96
	Real	142.10	39.56	28.95	0.00	81.25	17.36	52.43

Figure 6: Comparative table of glycemic outcomes for generated vs. real patients on sedentary and active days

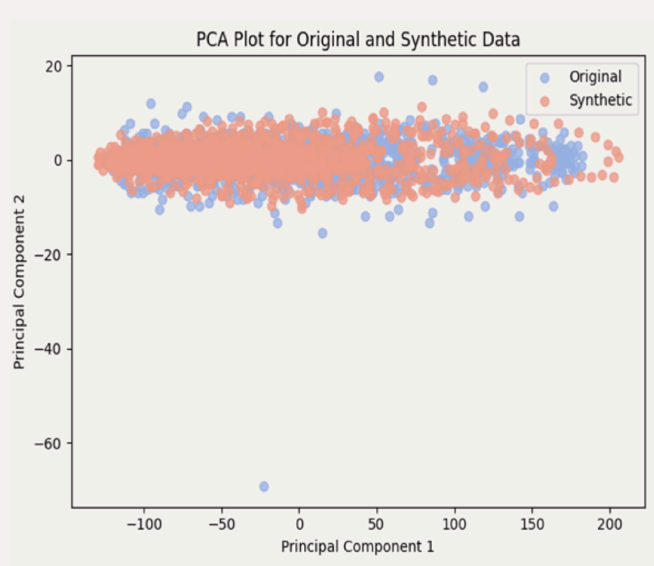

Figure 7: PCA analysis of of delayed embeddings of real vs. synthetic BG values for patient 50

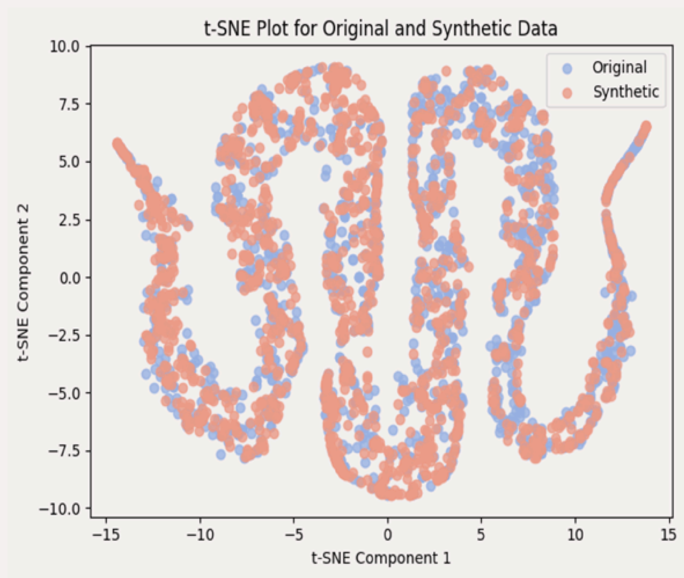

Figure 8: t-SNE analysis of delayed embeddings of real vs. synthetic BG values for patient 50

Conclusions

- Data-based virtual patients show potential in **predicting** exercise-induced **glycemic outcomes**
- Model realistically replicates glucose-insulin dynamics
- We are working on adding other exercise types included in T1DEXI

References:
[1] Pompa, Marcello, et al. "A comparison among three maximal mathematical models of the glucose-insulin system." PloS one 16.9 (2021)
[2] Mujahid, O., et al. "Generative deep learning for the development of a type 1 diabetes simulator". Communications Medicine, (51), (2024)
[3] Noguer J, et al. "Generation of Individualized Synthetic Data for Augmentation of the Type 1 Diabetes Data Sets Using Deep Learning Models". Sensors. (2022)

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