GlyMan: Glycemic Management using Patient-Centric Counterfactuals

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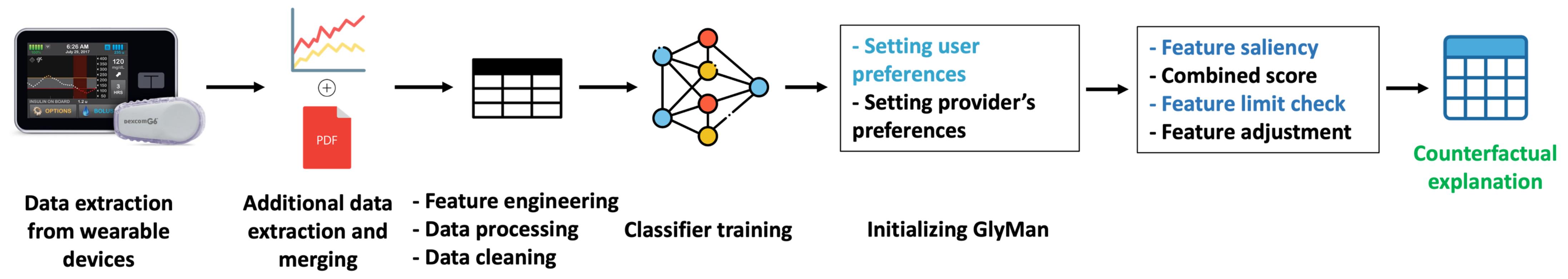
INTRODUCTION

Although, continuous subcutaneous insulin infusion (CSII) and continuous glucose monitors (CGMs) can forecast adverse events like hyperglycemia. However, these technologies cannot guarantee an optimal insulin dosage. This often leads to inappropriate insulin administration or even hypoglycemia. We pitch ***GlyMan,*** a counterfactual AI algorithm that generates alternative behavioral recommendations to help patients and caregivers make small, informed changes to patient behavior and reduce both the frequency and duration of hyperglycemia and hypoglycemia. GlyMan also integrates stakeholders' preferences to keep certain attributes unchanged while implementing interventions.

GlyMan records a high validation of 0.766 and a high NN-test score of 0.859 while achieving perfect violation and plausibility scores. GlyMan also surpasses relevant baselines like DiCE and NICE.

AIMS

1. Develop an iterative counterfactual AI algorithm that produces behavioral recommendations leveraging a classifier trained using demographic attributes and features calculated from the devices
2. Incorporate classifier, clinician, and patient’s choice on which features remain unchanged, ensure realistic interventions that avoid over-correcting the patient
3. Evaluate the interventions’ alignment with the stakeholders’ preferences and compare the results against the baselines.



DATASET

➔ **21** Type 1 diabetes patients who were monitored for **26** days in the wild

➔ Patients wore Dexcom G6 Pro for monitoring CGM and Tandem T:SLIM X2 Pump for administering insulin

➔ Converted the time-series data to meal events and engineered features like Insulin to meal time (Δt), Device mode, Total basal, and Pre-meal BGL slope

➔ Total 1361 meal events split following an **85:15** ratio for training and testing

TABLE I: Examples of processed samples from the dataset.

Age	Sex	Ethnicity	A1C	Carb size	Total bolus	Δt	Mode	Total basal	Pre-meal BGL slope	Pre-meal BGL	Outcome
61	F	White	6.7	20	7.57	-5	regular	2.475	2.943	129	normoglycemia
32	F	Hispanic	5	35	5.83	15	regular	0.357	1.457	134	hyperglycemia

Method

1. Design a classification model that predicts hyperglycemia or normoglycemia given a sample X_T

$$f : \mathbb{R}^d \rightarrow [1, c]$$

2. Gather physician and user’s weights (w_p and w_u) to know which features they prefer to change in the interventions
3. Leverage the classifier to get the saliency score for each modifiable feature

$$S(x_T, y', i) = \frac{f_n(x_T^{*i} + \delta_i) - f_n(x_T^{*i})}{\delta_i} \quad \forall x_T^{*i} \in x_{mod}$$

4. Create a combined saliency score for each modifiable feature

$$\text{combined saliency score} = |S(x_T^*, y', i)'| + (w_p + w_u)$$

5. Select the feature (i') with the highest combined saliency score and incrementally modify it using an iterative approach until a desired target probability is reached. Make sure the modification stays within the plausible range.

$$i' = \arg\max_i \left[|S(x_T^*, y', i)'| + (w_p + w_u) \right]$$

$$x_T^{*i'} = x_T^{*i'} + \delta_i \text{ s. t. } \mathfrak{f}_{min}[i'] \leq x_T^{*i'} \leq \mathfrak{f}_{max}[i']$$

Results

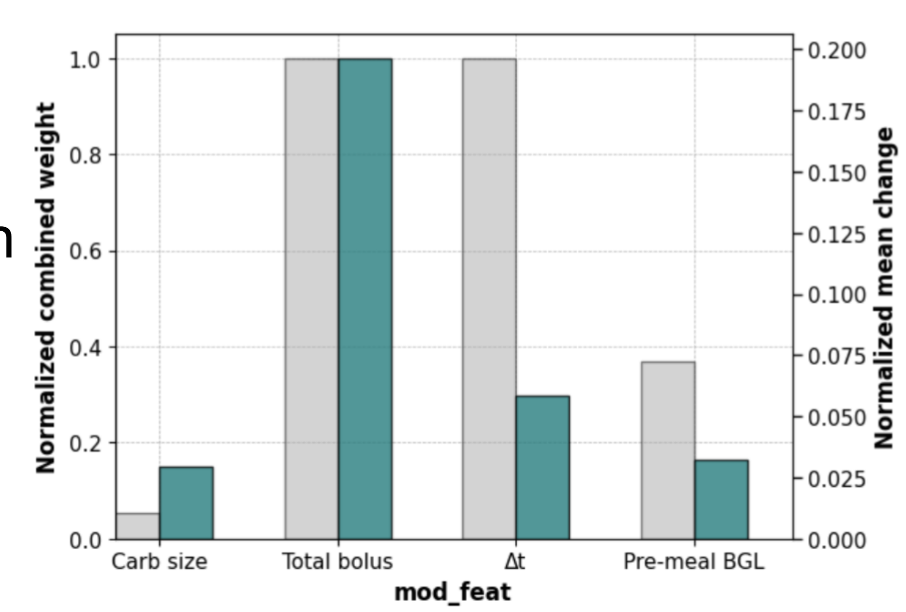
We validate GlyMan using traditional metrics like ***validity, proximity, sparsity, violations*** and ***plausibility***. We also have ***an NN-test,*** which looks at historical data to understand how this patient did in similar situations.

GlyMan tops the list in validity, NN-test, violations and plausibility but performs bad in terms of proximity score (nearness from the factual sample)

TABLE II: Evaluating the counterfactuals from GlyMan using validity, NN test, proximity, violations and plausibility.

Method	Mayo Clinic Data					
	validity	NN test	proximity	sparsity	violations	plausibility
GlyMan	**0.766**	**0.859**	0.327	2.34	**0**	**1.0**
DiCE	0.703	0.813	0.333	1.63	**0**	**1.0**
NICE	0.688	0.688	**0.179**	**1.875**	0.41	0.9

The preference alignment bars show that the normalized combined weights from the physician and the user is correlated to the normalized change to the features despite there is an additional influence of feature saliency.



Preference alignment analysis of GlyMan.

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