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# **Explainable Artificial Intelligence to predict clinical outcomes** for adults with Type 1 Diabetes

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#### Introduction

Type 1 diabetes patients are prone to life-threatening con-

### Experimental data set

The experiments of this study are based on the T1D exchange clinic registry open data set that contains 25759 T1D patients data gathered from 67 clinical centers in the United States. This study focuses on 7,155 people in the registry, aged 26 to 93 years and had a T1D duration of at least two years.

ditions. Severe hypoglycemia (SH) and diabetic ketoacidosis (DKA) are such conditions that often require urgent hospital care. The objective of this study is to implement an AI-based explainable solution to predict possible SH and DKA events in T1D patients within the next 12 months. The initial models of this study were built with baseline factors identified in prior research. These models were further improved by introducing more features and separating the population by gender. The final models were used to build a decision support system that facilitates precision medicine by prioritizing the high-risk patient group. In addition, it helps to potentially reduce medical expenses through more efficient resource management.

## **Experiments and Results**

In the initial step, the models were developed using the features mentioned in the replication study.

#### Prediction models with prior study findings Both the SH and the DKA prediction models were built with 13 baseline features including patients' socioeconomic status,

## **DKA Model Interpretation**

In this study, we are trying to bridge the interpretability gap in medical machine learning using the SHAP library. Global interpretation is achieved by using the SHAP information densesummary plot. That gives a view of how features and their values impact on model outcomes across the whole dataset. It is important to have a reason for each individual's outcome separately. Local interpretability is achieved by reviewing the Shapley values of each prediction. It expands the interpretability of the model by predicting possible risks and providing the reasons behind the prediction.



such as annual income, private insurance, and education level.

	Model	Class wise		Balanced		Predicted		$\mathbf{F1}$
		accuracy		accuracy		labels		score
		Docitivo	Nocativo			Positive	Negative	
		POSITIVE	negative			(P)	(N)	
					Р	39	12	
SH	$\mathbf{LGBM}$	0.76	0.57	0.66	Ν	<b>692</b>	921	0.72
					Р	<b>35</b>	15	
DKA	AdaBoost	0.70	0.64	0.67	Ν	<b>527</b>	966	0.64

Table 1:Results of the models with baseline factors

#### **Prediction Models with Improvements**

The best results for SH prediction were achieved with genderdisaggregated models that use 147 features to predict the outcome. A single prediction model that used all the features in the preprocessed data set achieved the best result in predicting DKA events.

(a) Global interpretation (b) Local Interpretation Figure 1:Gloabal and Local interpretation of DKA model

# **Decision Support System**

The implemented models were used to build a decision support system for health care personnel. The main objective of this system is to identify patient's risk categories of developing DKA events in the future.



Defined threshwere used

	Model	Class wise accuracy		Balanced	Predicted			$\mathbf{F1}$
				accuracy		labels		score
		Positive	Negative			Positive	Negative	
						(P)	(N)	
					Р	20	0	
SH Male	LGBM	1.0	0.72	0.86	N	<b>205</b>	530	0.73
					Р	23	4	
SH Female	LGBM	0.85	0.72	0.78	N	<b>243</b>	634	0.72
					Р	44	6	
DKA	LGBM	0.88	0.77	0.82	N	340	1153	0.77

Table 2:Results of the final models