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Using Explainable Machine Learning for Diabetes Management at Emergency Department

By

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Artificial Intelligence for Diabetes Management

What is know about Diabetes Mellitus (DM)?

- Three types of diabetes (Type 1, Type 2, Gestational)
- A progressive disease
- DM is not reversible
- DM management is patient centric
- DM affects the use of blood glucose
- DM affect blood flow in small vessels
- Uncontrolled diabetes leads to complications
- Uncontrolled diabetes leads to emergency cases with risk of ICU

AI in Diabetes Management

- Lots of data for diabetes patients
- Historical DM data can be used for automated screening
- Early detection of complications
- Early preparation of emergency cases
- Detect adverse effects of drugs
- Glucose monitoring
- Patient education and follow-up

Target: Diabetes care for a near-normal life

Diabetes Management: Call for Action

Diabetes cases continue to rise

536 Million in 2021

783 Million in 2045

Preparedness

?

AI has the potential to transform Medicine, Medicine can drive changes in AI

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Research: Explainable Machine Learning to predict ICU admission and estimate length of stays.

Methods

- MIMIC-IV Diabetes Emergency Data extracted using ICD-Code (E10.XXX for T1DM and E11.XXX for T2DM)
- Boosted tree ensemble models
- Predict ICU admission
- Estimate length of stays for ICU admitted patients
- Provide explanations using SHAP methods

Objectives

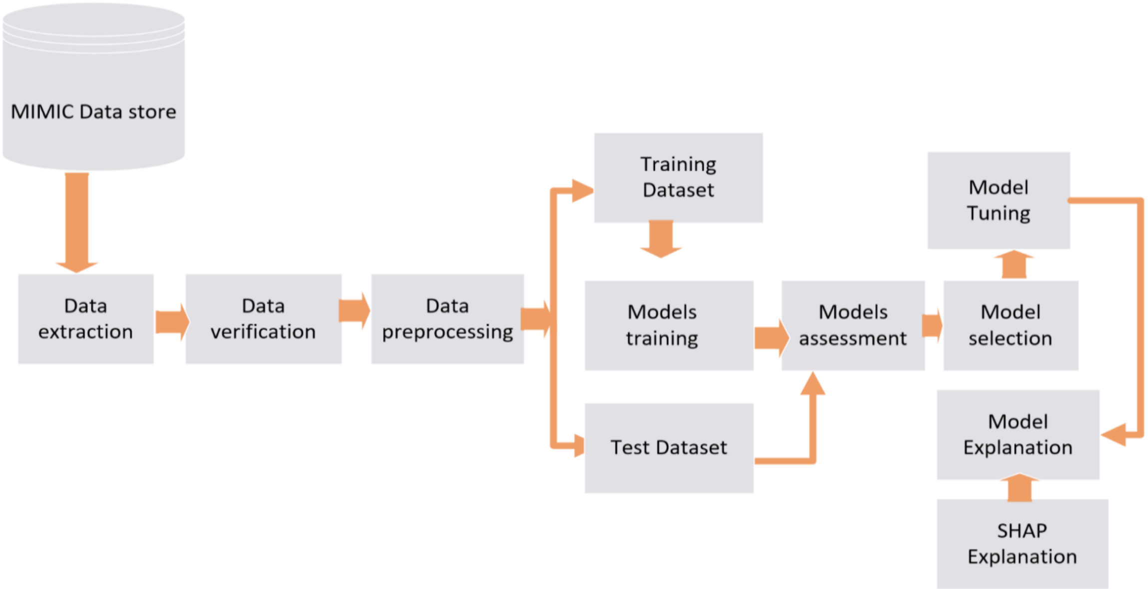
1. Develop boosted tree-based ensemble ML models using ED data to predict ICU admission risk for T1DM and T2DM patients,

2. Build ML model to estimate the length of hospital stays for diabetes patients upon ED admission

3. Apply SHAP methods to provide interpretable explanations for the classification and regression models predicting ICU admissions and length of stay

Explainable ML to early identify diabetes patients at risk of ICU and estimate length of stay

Research Design



After Data Preprocessing: 1. Dataset of 40,55 samples and 49 features for ICU Prediction, 2. Dataset for LOS estimation (1432 samples, 49 features), 5 ML Models (Decision Tree, AdaBoost, CatBoost, XGBoost, LightGBM), and TreeSHAP for Explanations.

Data Preprocessing

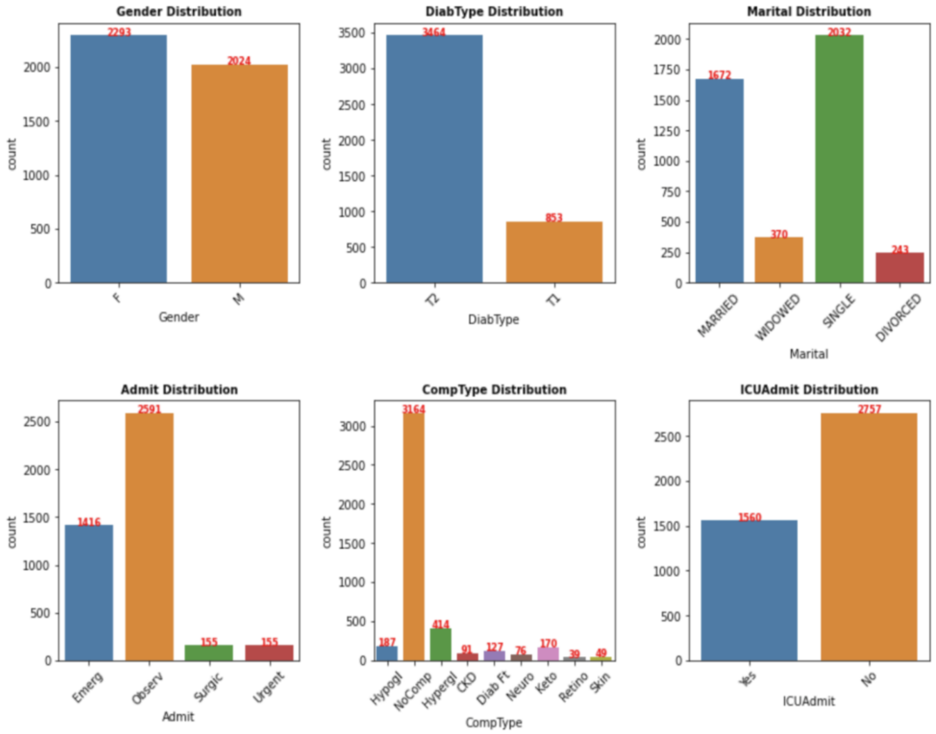


Figure 3. Visualizing the distribution of categorical data.

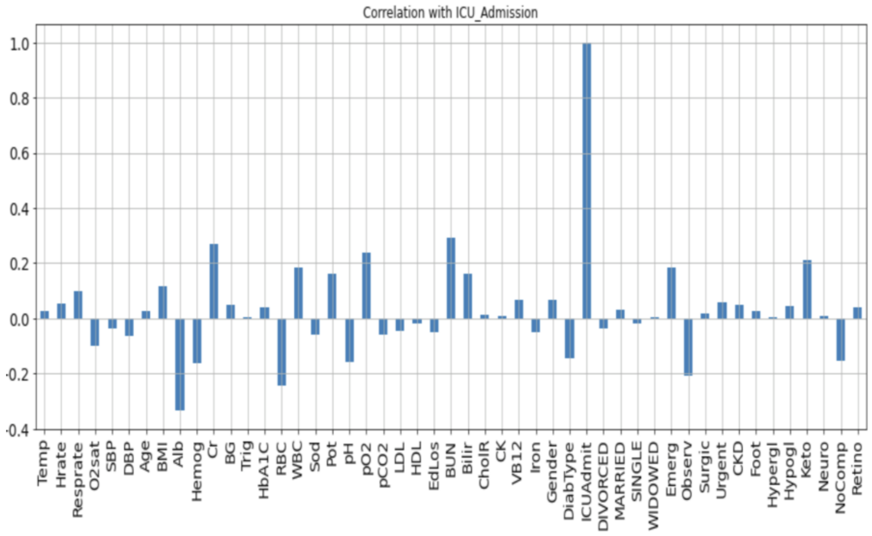


Figure 4. Features correlation to the ICU admission.

Abbreviations: Temp: Temperature, Hrate: Heart rate, Resprate: Respiration rate, O2sat: Oxygen saturation, SBP: Systolic blood pressure, DBP: Diastolic blood pressure, BMI: Body mass index, Alb: Albumin, Hemog: Hemoglobin, Cr: Creatinine, BG: Blood glucose, Trig: Triglycerides, HbA1C: Glycated Hemoglobin, RBC: Red blood cells, WBC: White blood cells, Sod: Sodium, Pot: Potassium, pO2: Partial pressure of oxygen, pCO2: Partial pressure of carbon dioxide, LDL: Low-density lipoprotein sometimes called bad cholesterol, HDL: High-density lipoprotein known as good cholesterol, BUN: Blood urea nitrogen, Bilir: Bilirubin (Total), CholR: Cholesterol ratio, CK: Creatinine kinase, VB12: Vitamin B12.

Results and Discussion(ICU Admission Prediction)

Table II. MODEL PERFORMANCE ON ICU ADMISSION PREDICTION

Classifier	Accuracy	Precision	Recall	F1-score	AUC
Decision Tree	74.60	66.33	64.57	65.44	0.726
XGBoost	80.76	77.24	68.54	72.63	0.861
CatBoost	82.24	79.04	71.19	74.91	0.882
LightGBM	81.75	78.73	69.87	74.04	0.869
AdaBoost	**82.74**	**80.92**	**70.20**	**75.18**	**0.876**

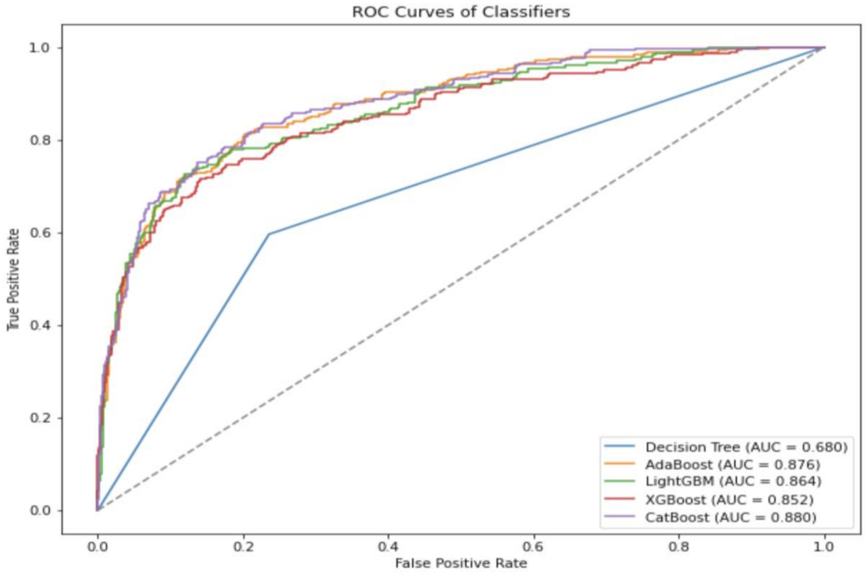


Figure 5. ROC Curve of ML models used to predict ICU admission with AUC between 0 and 1

Discussion: Selected models performed well in ICU admission prediction, AdaBoost showed superior performance in 3 out of 5 model evaluation metrics. AdaBoost was selected and fine-tuned to identify diabetic patients at risk of ICU admission.

Results and Discussion(ICU Admission Prediction cont'd)

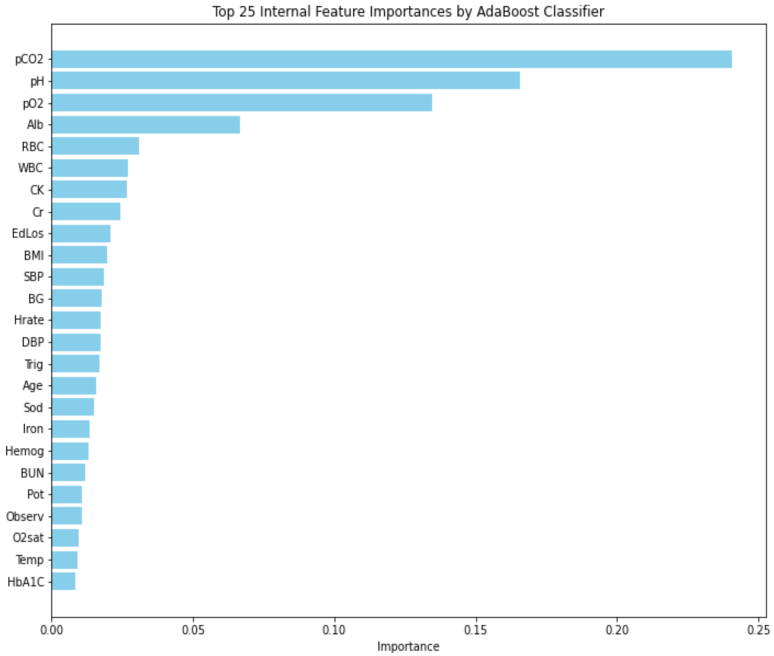


Figure 7. (a) Top 25 predictors by AdaBoost.

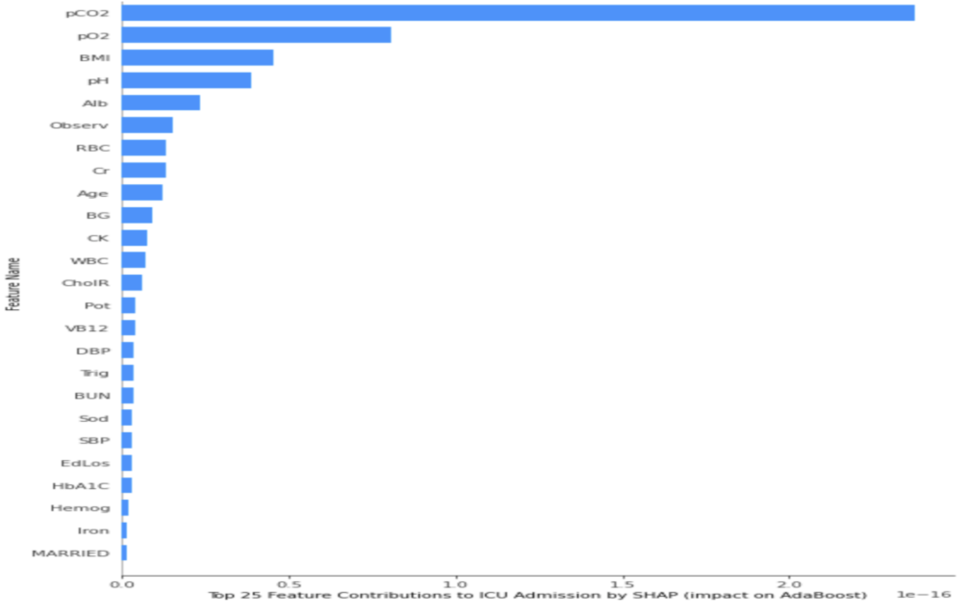


Figure 7. (b) Top 25 predictors by SHAP.

Table III. ADABOOST PREDICTIVE PERFORMANCE USING FEATURES IDENTIFIED BY THE SHAP METHOD.

Classifier	Accuracy	Precision	Recall	F1-score	AUC
AdaBoost	82.74	77.01	73.26	75.09	0.881

Discussion: We generated 25 feature importance driving the ICU admission prediction outcome using Model-based and SHAP Methods, the best model was retrained on 25 features identified by SHAP and achieved slightly similar results.

Results and Discussion(ICU LOS Prediction)

Table V. RSME AND MAE FOR FIVE REGRESSION MODELS WHILE ESTIMATING ICU LOS.

Regression Model	**RMSE**	**MAE**
CatBoost	2.454	1.695
LightGBM	2.739	1.937
XGBoost	2.863	1.951
Decision Tree	4.547	2.521
AdaBoost	4.864	4.537

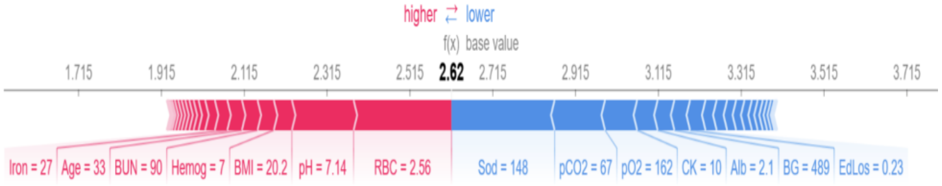


Figure 8. The SHAP force plot explaining ICU LOS for the patient on row number 51 in the test set.

Discussion: The best model (CatBoost) for estimating the length of stays for ICU admitted patients got 2.454 and 1.695 for Root Mean Squared Error and Mean Absolute Error in days at the Hospital. We used SHAP methods to provide local explanations of predicted LOS for individual patients. Figure 8 in the paper visualizes the features contributing to the predicted LOS, features in red color increasing the hospital stays.

Results and Discussion(ICU LOS Prediction Cont'd)

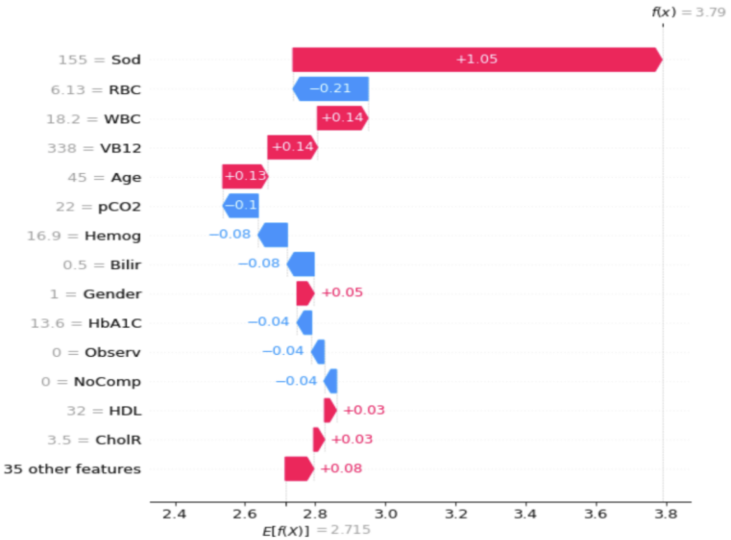


Figure 9. SHAP waterfall plot for estimating ICU stays for a patient with row 241 in the test set.

- SHAP gives details explaining why patient in Figure 9 was predicted to stay in the ICU for 3.79.
- SHAP highlighted features mostly contributing to extended length of stays at hospital.
- This patient has abnormal sodium of 155 (normal range: 135-145)
- poor control of blood sugar levels (BG of 264 and HbA1C of 13.6).
- The patient has pCO2 of 22 (very low, normal range: 35-45). pCO2 was the leading top predictor for ICU admission
- The patient has Ketoacidosis complication, a major cause of prolonged stays in ICU among diabetic patients

Discussion: Experimental results on ICU stay estimation indicate that the CatBoost model, and SHAP-based explanations, is well-suited for supporting ICU bed allocation decisions following the collection of patient demographic, vital signs, and laboratory data.

Discussion

Table IV. ANALYSIS OF SHAP EXPLANATIONS BY CLINICIAN

No.	Model's top five	Clinician's top 5	Agreement
1	pCO2	BG	No
2	pO2	pO2	Yes
3	BMI	BMI	Yes
4	pH	Cr	No
5	Alb	Alb	Yes

- A clinician contributed to the selection of features for model training
- A clinician identified the top 25 features most correlated with ICU admission
- Comparison of the clinician's and SHAP's top 25 features revealed substantial agreement
- Discrepancies were observed between the clinician and SHAP in the ranking of the top 5

Discussion: Explanations generated by SHAP provide clinically interpretable insights and can support informed decision-making regarding ICU admission.

Conclusion and Future Research

Conclusion: The experimental results successfully addressed the study's objectives:

1. develop a predictive model for ICU admission at emergency department,
2. develop a predictive model for length of stay estimation among diabetic patients at emergency department,
3. Generating interpretable explanations using SHAP.

Key Findings:

- *ICU Admission Prediction*: AdaBoost demonstrated the highest predictive performance on ICU admission.
- *ICU Length of Stay Estimation:* CatBoost outperformed other models.
- *Feature Interpretability:* SHAP identified the top 25 influential features for ICU admission prediction.
- *Clinical Validation:* A clinician with over 15 years of experience largely agreed with SHAP's feature importance, noting only minor differences in top feature rankings.

Recommendation:

- Emergency departments should prioritize laboratory assessments of pCO_2, pO_2, BMI, Blood Glucose, Creatinine, Albumin, and pH for diabetic patients presenting in emergency settings.
- This prioritization may improve the early identification of patients at risk of ICU admission and enhance the quality of emergency care for diabetes patients.

Future Work:

- Integrate pretrained models into a web-based application for deployment in emergency departments.
- Assess the impact on emergency diabetes care and the trust level among healthcare providers.

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Thanks, Murakoze, Merci, Tack!

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