Your Diabetes treatment Xplained

Problem:

We aim to use a set of explainability methods to assess whether a diabetes patient is likely to be readmitted to the hospital within 30 days.

Objective:
- Generate a set of rules from the features and extract the causal relationships between the features that explain a certain outcome in time.

Impact:
- Analyse and evaluate hospitals' level of care of the patients to provide insightful explanations both to the patient and the hospital.

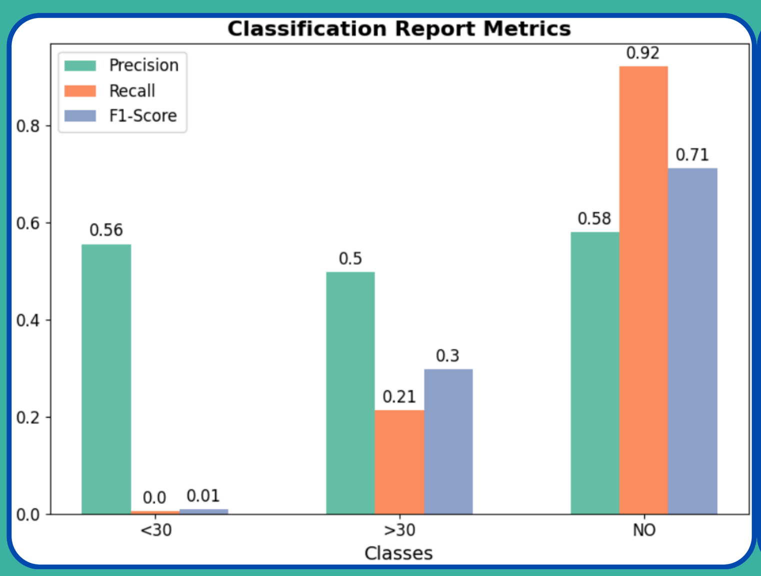
Research Question 1:

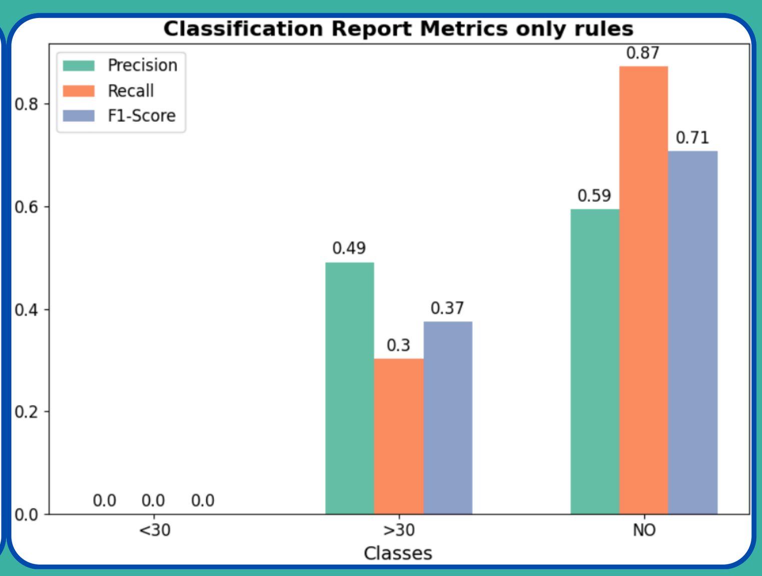
What are the factors that contribute the most over time to the doctor's decision on readmitting a diabetes patient?

Methodology: RuleFit and Bayesian Networks

1. Loaded and preprocessed the training and test datasets, using the filtered features
2. Split the training data into training and test sets using an 80-20 split.
3. Trained a RuleFit model on the training data and evaluated its performance on the test set. We use RuleFit in order to get intelligible rules to make a decision.
4. Trained a Tree-Augmented Naïve Bayes (TAN) on the training data and validated it's performance on test set. We used TAN to understand the dependencies among the features and their csual relationship with respect to the readmission decision.

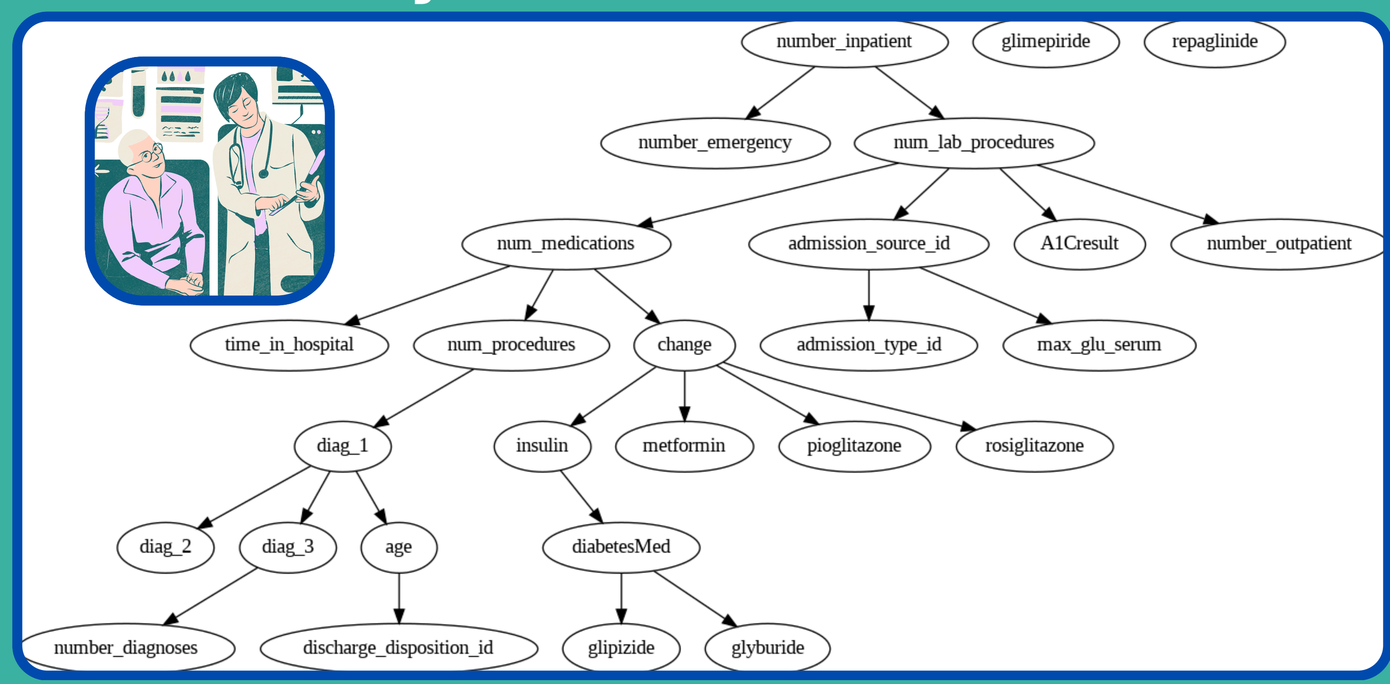
Results: RuleFit





+ Rules for every class

Results: Bayesian Networks



TAN: 55.58%, FAN: 61.65%

Class Pred Score

TAN <30: 0.112, >30: 0.353, NO: 0.534

FAN <30: 0.114, >30: 0.349, NO: 0.536

Conclusions: RuleFit

- The RuleFit classifier achieved an accuracy 57% on the test set.
- The performance on the <30 class is significantly worse compared to >30 and NO.
- RuleFit with only rules does not work for the <30 class.

Conclusions: Bayesian Networks

- The Forest Classifier performed better than the Tree Classifier as expected: the features interactions are approximated by an **ensemble tree** imposed on a Naive Bayesian structure. TAN is a more restricted form of correlation edges. Both improve perfromances by **removing the features**.
- Bayesian Networks require searching the space of all possible networks (combination of edges): **>40min**, TAN/FAN classifiers can be learned in a **polynomial time**! **~300ms**

Discussion RQ1

1. Role of RuleFit

RuleFit **provides intelligible rules and heuristics** based on otherwise hard to interpret set of features. A rule can be comprised of multiple subrules. This can used to match based on feature similarity at which point of time of a patient's medical record a certain decision is likely to be taken. Alternatively, reasoning on the global stats of the rules may help in providing context to hospital's treatments.

2. Role of Bayesian Networks

A Bayesian Network provides the (conditional) dependencies graph, which represents the causal relationships between the variables. These causal relationships can be used to **verify the causal validity** of the (sub)rules provided by RuleFit.

Research Question 2:

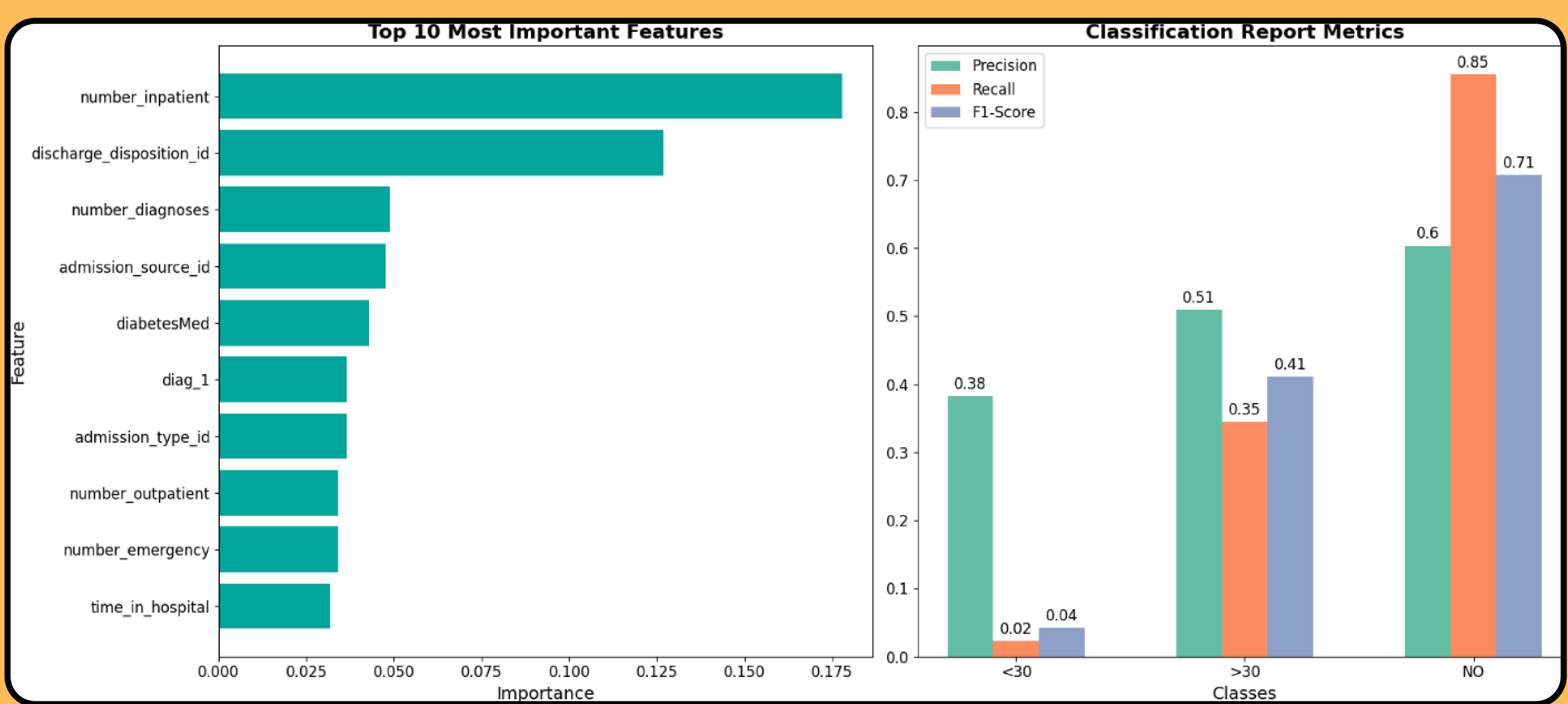
What are patient and clinical features that influence readmission risk in diabetic patients?

Impact: Helping medical experts tackle inadequacies in the provided healthcare based on recurring patterns across all patients

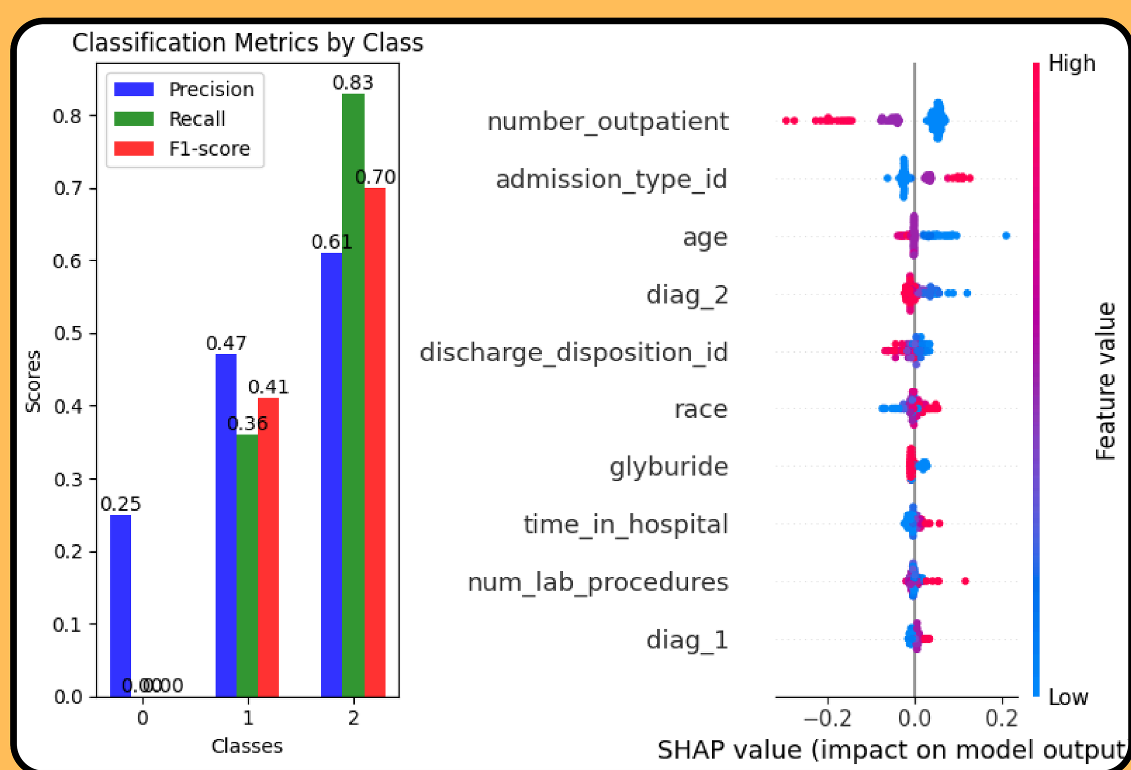
Methodology: Explainable Boosting Machine and Neural Network

1. Loaded and preprocessed the training and test datasets, using the filtered features
2. Split the training data into training and test sets using an 80-20 split.
3. Trained an Explainable Boosting Classifier (EBM) model on the training data and validated its performance on the test set.
4. Trained a neural network on the training data and validated its performance on test set. We used SHAP to understand the relevance of features on the final outcome using the datapoints from test set.

Results: EBM



Results: NN



Conclusions: EBM

- The Explainable Boosting Classifier achieved an overall accuracy of 58% on the test set.
- For predicting readmission within 30 days (class 0), the precision was 0.44, recall was 0.03, and F1-score was 0.06. For predicting readmission after more than 30 days (class 1), the precision was 0.50, recall was 0.33, and F1-score was 0.40. For predicting no readmission (class 2), the precision was 0.60, recall was 0.86, and F1-score was 0.70.
- The top three most important features were number_inpatient, discharge_disposition_id, and number_diagnoses, with number_inpatient being the most influential.

Conclusions: NN

- The Neural Network Classifier got a final accuracy of 58% on the train set and an accuracy of 52% on the test set .
- The neural network achieved low performance on class 0(precision=0.25 and recall=0), however the network shows better performance for class 1(precision0.47 recall=0.36) and class 2(precision=0.61 and recall=0.83).
- The top three most important features were number_inpatient, admission_source_id, and discharge_disposition_id , with number_inpatient being the most influential.

Discussion RQ2

1. Similarities in important features

Both models highlight the importance of 'discharge_disposition_id' and 'time_in_hospital;, suggesting consistent influence on predictions. An interesting different is the fact that the EBM model emphasizes on 'number_inpatient' and "number_diagnoses', while the Neural Network focuses on "number_outpatient", and demographic factors such as "age" and "race", reflecting different prioritization of features. Unique features like "diabetesMed" for EBM and "glyburide" for the Neural Network demonstrate each model's distinct pattern recognition. These differences underline the complementary strengths of the models, offering deeper insights when used together and could be an addition to expert insights.

2 Why are precision and recall low for class 0?

The number of instances of class 0 (7753) are pretty low as compared to that of class 1 (24503) and class 2 (37331). This leads the model to be biased for class 1 and 2 which consecutively affects the metrics for class 0.