Technische Universität Braunschweig

Medizinische Hochschule Hannover

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Diabetes Readmission Prediction

By

Alisha Sarkar, Rabiya Farheen, Rajanigandha Dutt, Ria Mohan, Athira Sadhasivan

Objective

To build predictive models that determine whether a diabetic patient will be **readmitted within 30 days** of discharge.

Dataset

- We use the **Diabetes 130-US Hospitals** dataset from the **UCI ML Repository**.
- It contains **101,766 hospital records** of diabetic patients.
- Includes features like **age, gender, lab results, medications, diagnosis, and readmission status**.

Tasks

- Exploratory Data Analysis (EDA)
- Predict Readmission & Length of Stay
- Analyse Risk Factors
- Medication Impact
- Patient Grouping
- Demographic & Treatment Differences

Proposed Methodology

Exploratory Data Analysis

Data preprocessing

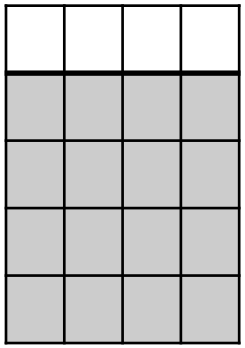
Train-test Split

Train the Model

Evaluate the Model

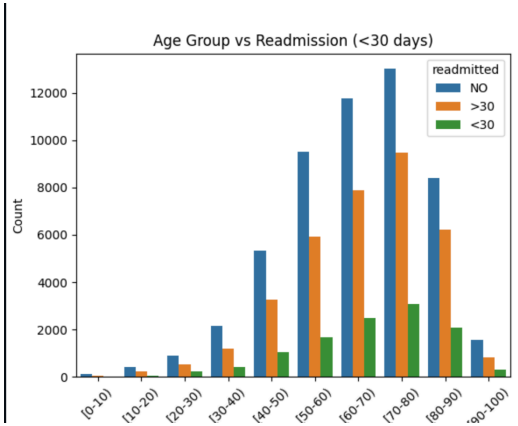
Exploratory Data Analysis

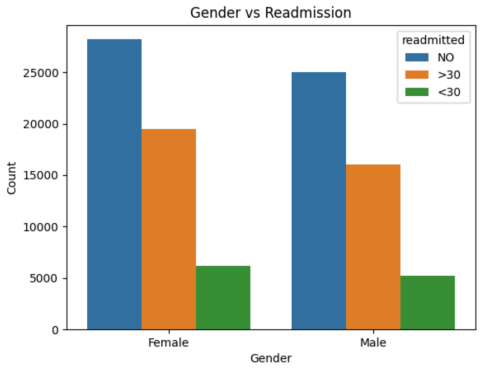
Data

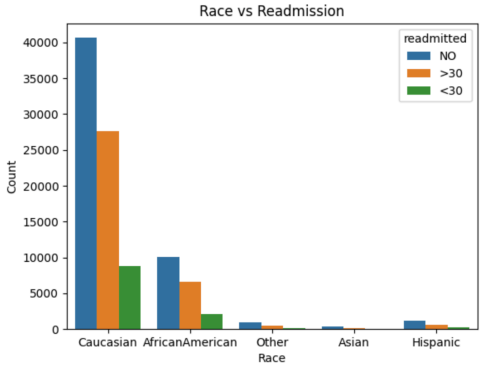


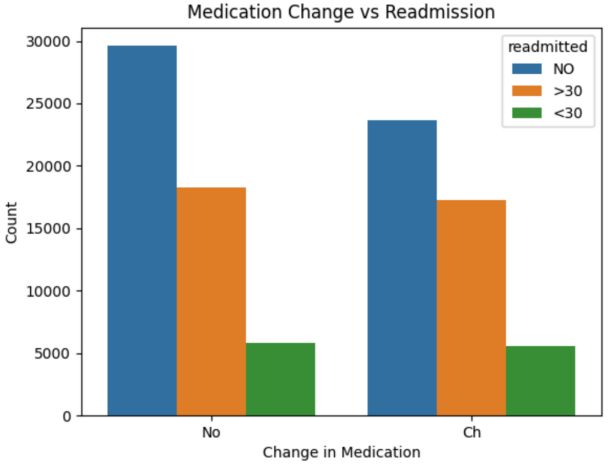
Visualising the data

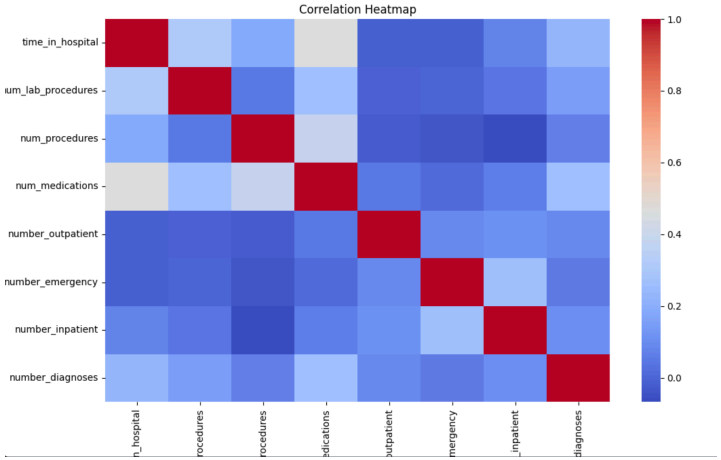
EDA Insights from the project











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Data Preprocessing

Transform raw patient data into a clean, structured format ready for modeling.

Raw Data →

Clean →

Feature Mapping & filter→

Encoding and Transformation →

Save

Data Split for Model Training

Load Clean Data:

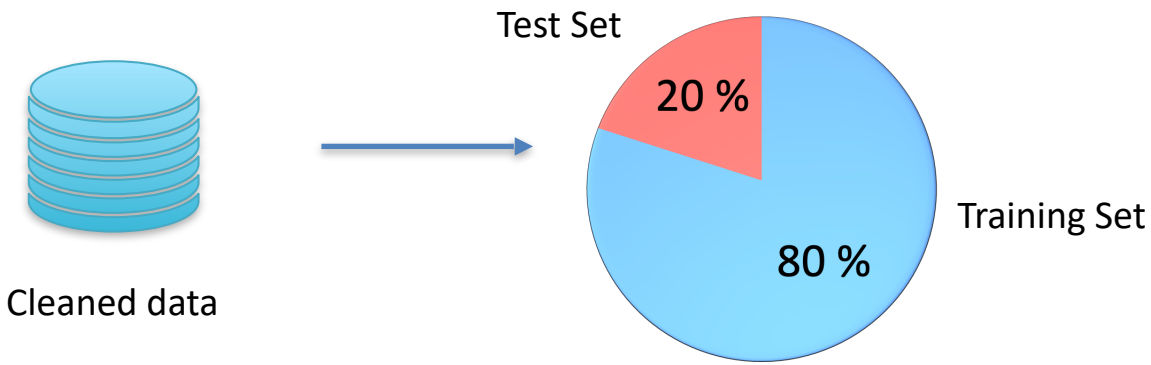
- Read the cleaned dataset.

Define Features & Target:

- X → all relevant features (demographics, labs, meds).
- y → target variable: **readmitted_30days**.

Train-Test Split:

- 80% training, 20% testing.



Model Training - Logistic Regression

What is it?

- A **supervised classification algorithm** used to predict a **binary outcome** (e.g., readmitted: **Yes/No**).

How does it work?

- Estimates the **probability** that an observation belongs to a class using a **logistic (sigmoid) function**.
- Outputs probabilities → applies a **threshold** to classify into **0 or 1**.

Why use it?

- Simple, **interpretable**, and works well as a **baseline model**.
- Coefficients show **feature impact** on readmission risk.

Model Training - Random Forest

What: An ensemble of many decision trees.

How: Builds trees on random data & features, combines votes.

Why: High accuracy, reduces overfitting, shows feature importance.

Model Training - XGBoost

What: Extreme Gradient Boosting

How: Builds decision trees **sequentially**, each new tree **corrects errors** of previous ones.

Why use it: High predictive **accuracy**, handles missing data well, faster and more efficient.

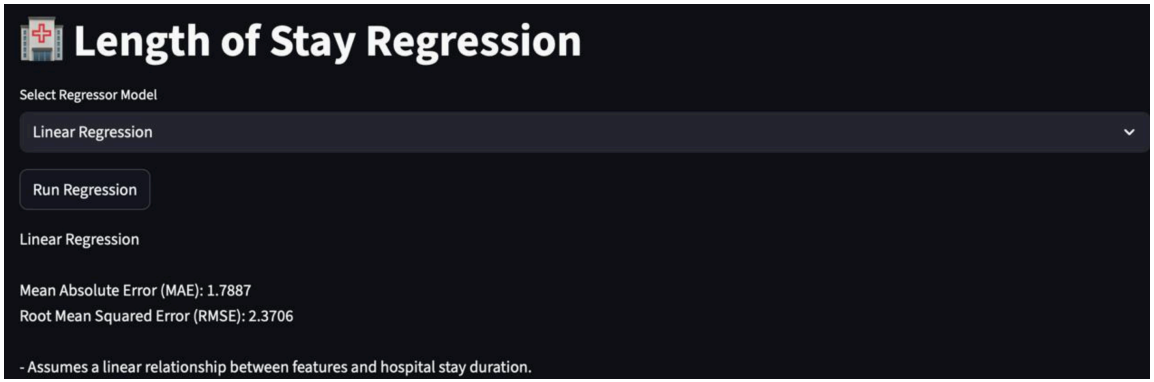
Prediction of Readmission and Length of stay

Goal: Predict if the patient is readmitted and for how many days a diabetic patient is likely to stay in the hospital.

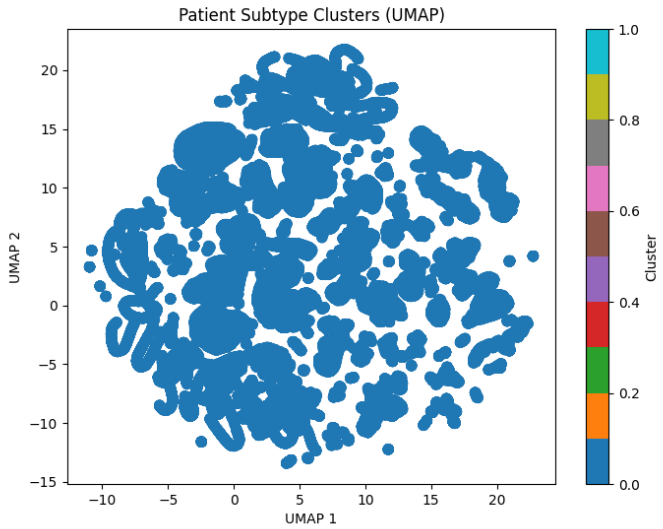
Why?

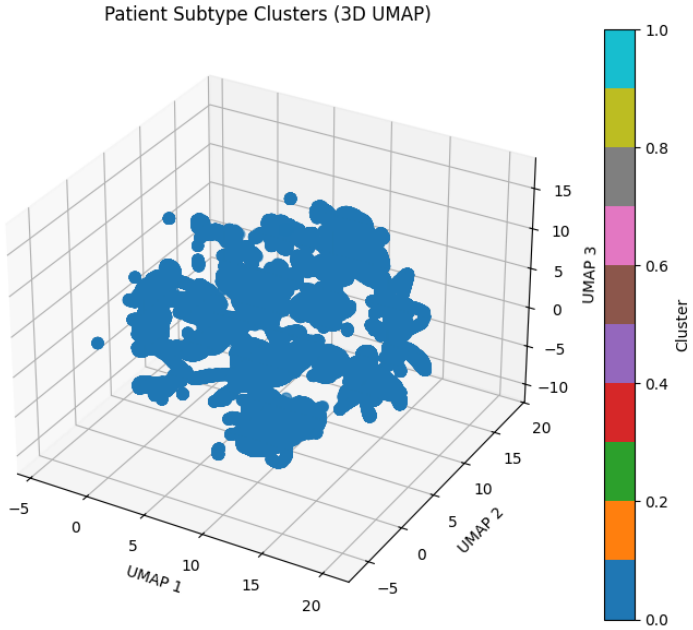
- Helps hospitals plan beds & staff.
- Supports better patient care.
- Can reduce unnecessary costs.

Prediction of Readmission and Length of stay



Insights - Patient Grouping





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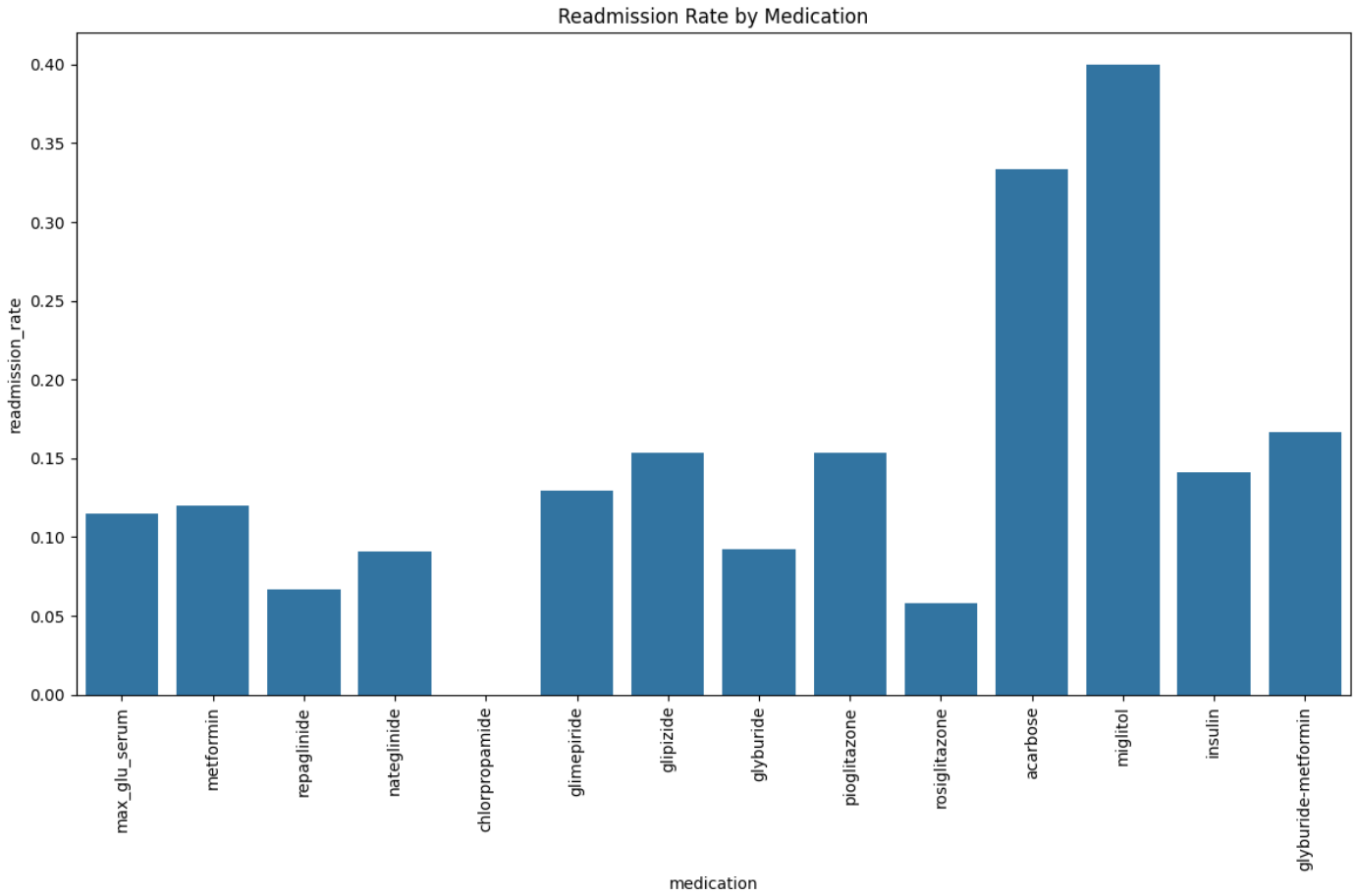
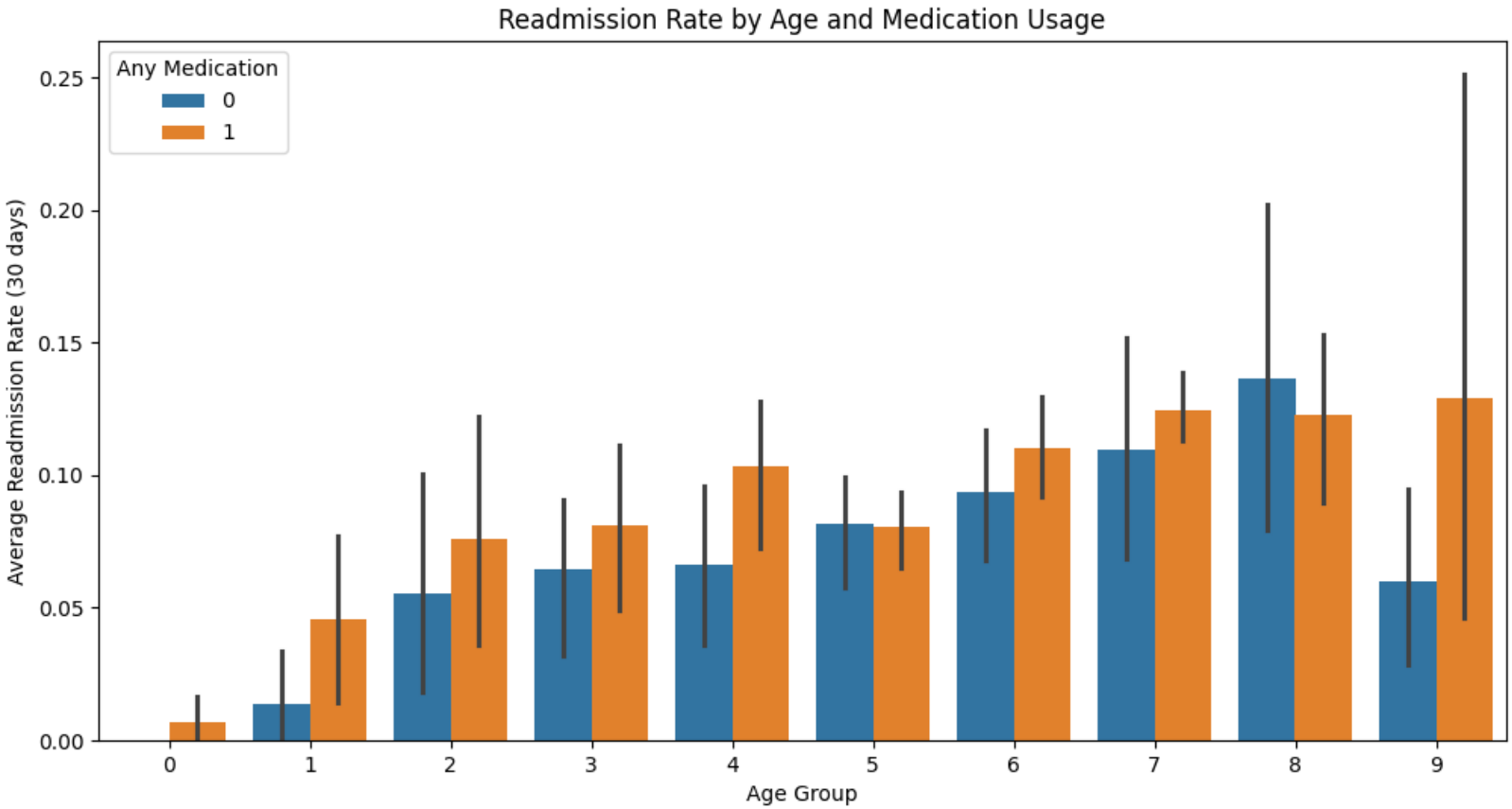
Medication Impact



Analyse Risk factors



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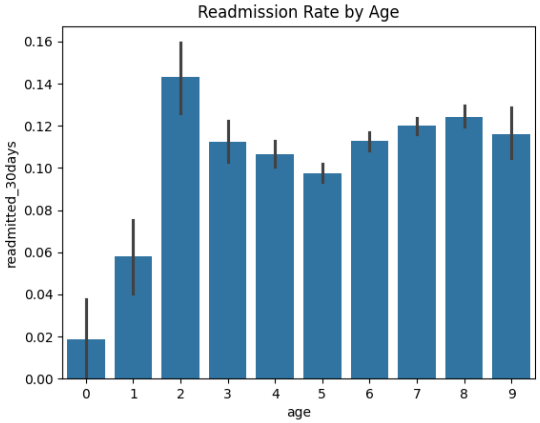
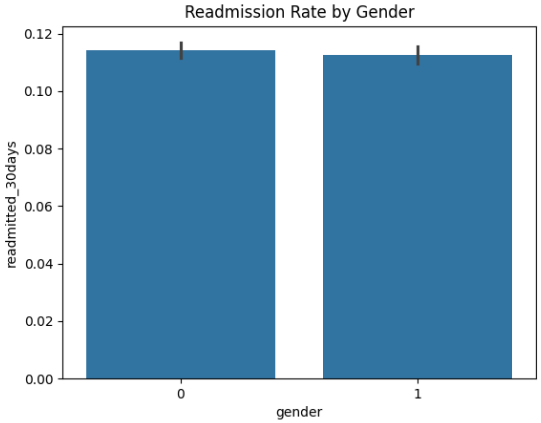
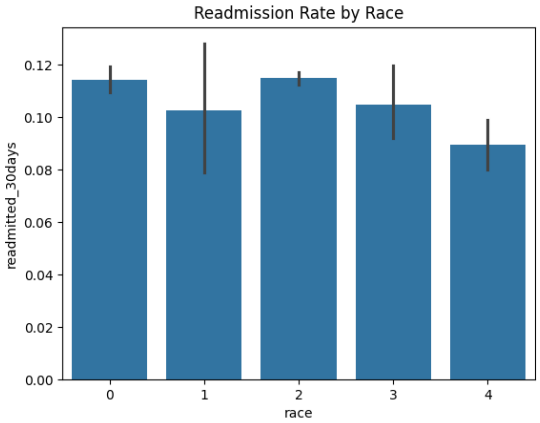
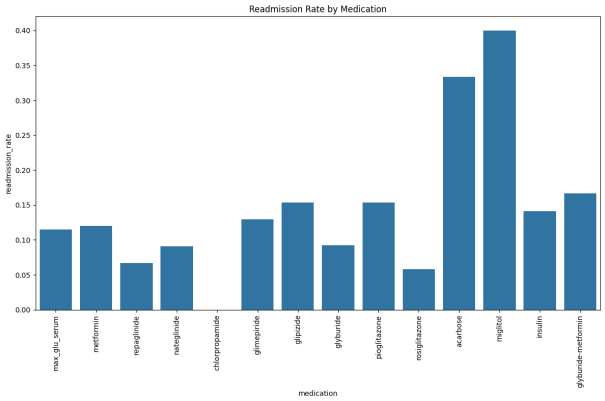
Demographic & Treatment Differences

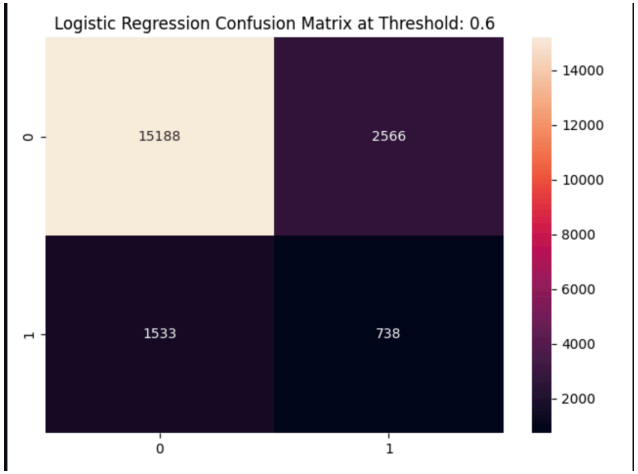


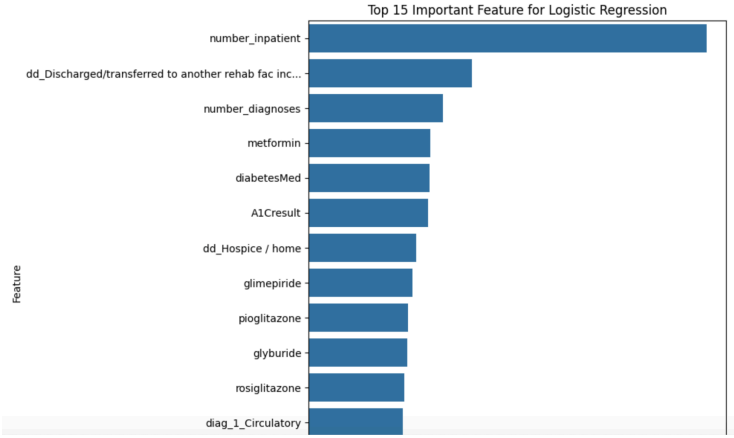


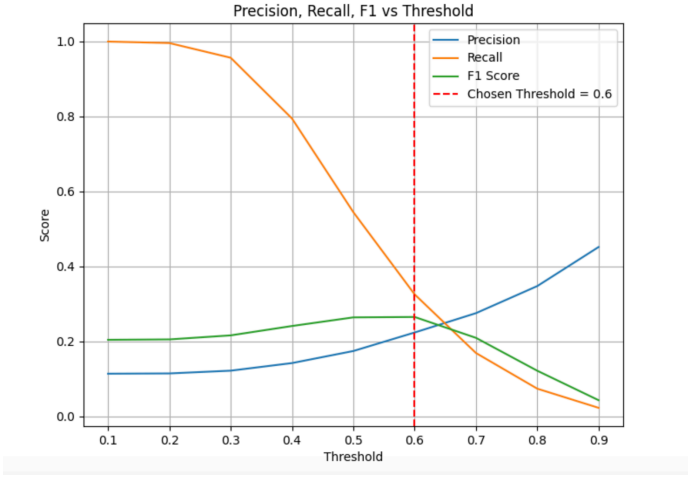




Model Training - Logistic Regression







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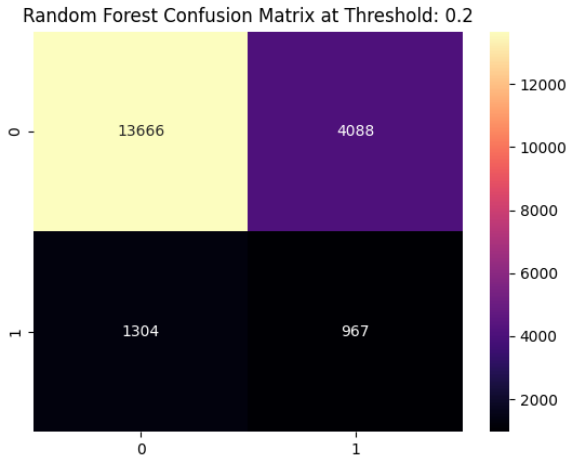
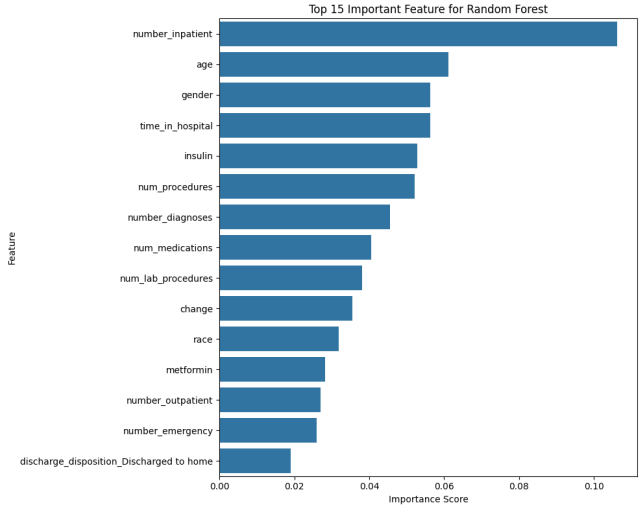
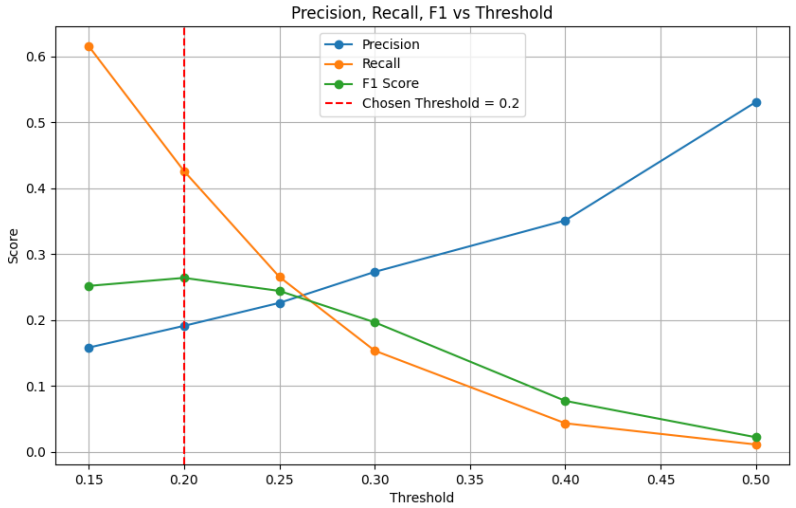
Model Training -Random Forest







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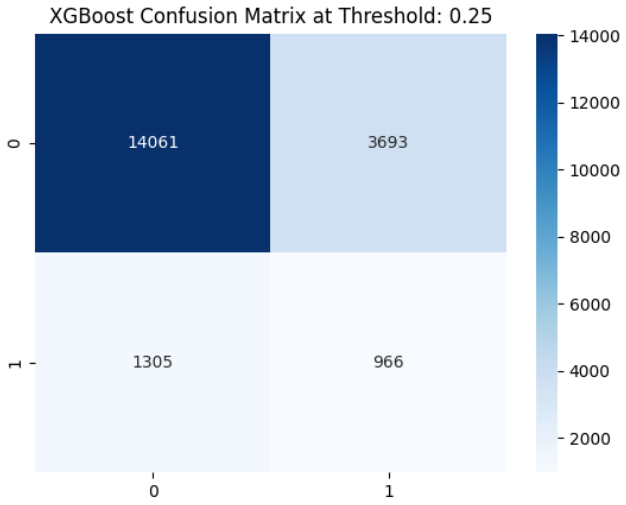
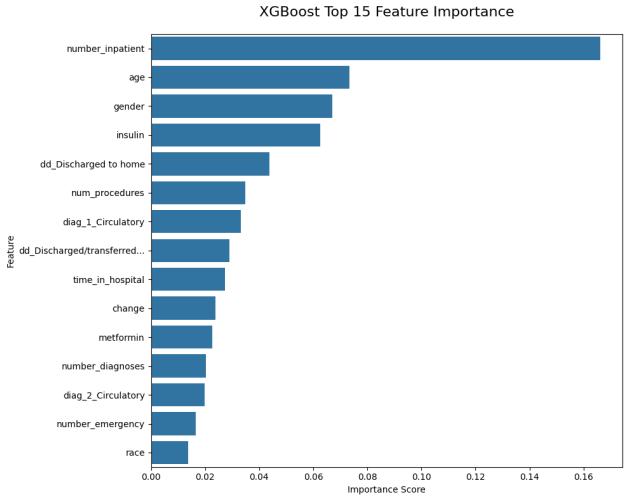
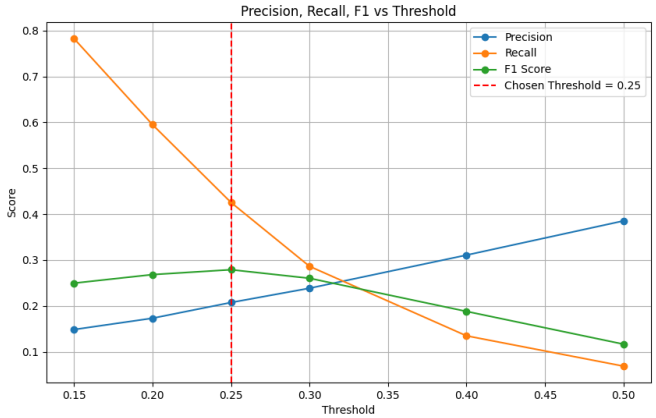
Model Training - XGBoost







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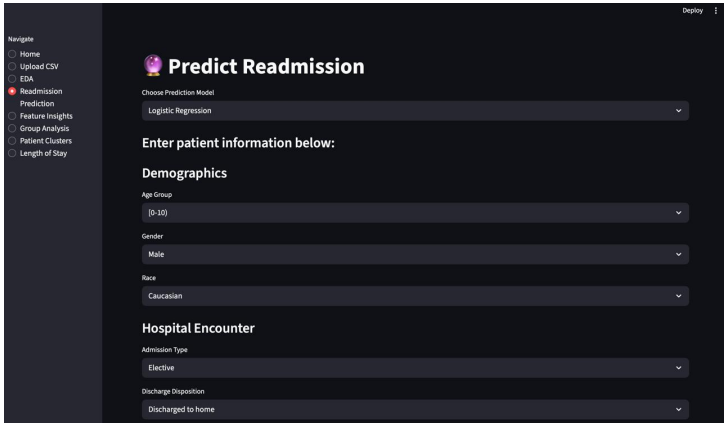
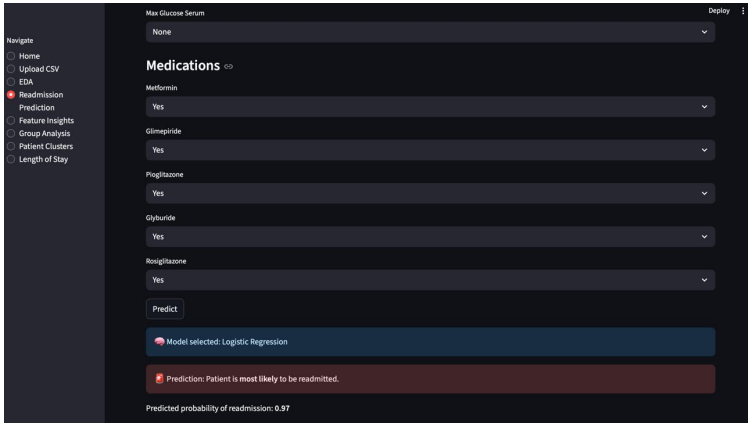
GUI Snapshots





Challenges

Data Challenges (EDA)

- Dealing with **missing values** in patient records.
- Handling **imbalanced classes** (very few readmitted vs. many not readmitted).
- Understanding & cleaning **categorical variables** (e.g., discharge status, admission type).

Feature Engineering

- Selecting meaningful variables among many hospital & treatment factors.
- Encoding complex categorical features correctly.
- Reducing high cardinality (e.g., diagnosis codes).

Model Training

- Avoiding **overfitting** with small/imbalanced data.
- Tuning hyperparameters for models like **XGBoost** and **Random Forest**.
- Choosing **thresholds** to balance **precision & recall**.
- Ensuring **interpretability** (doctors need to trust the model's decisions).

References

[1]Kansagara, D., Englander, H., Salanitro, A., Kagen, D., Theobald, C., Freeman, M., & Kripalani, S. (2011). Risk prediction models for hospital readmission: A systematic review. *JAMA*, 306(15), 1688–1698. https://doi.org/10.1001/jama.2011.1515

[2]Hasan, M. M., Haque, M. M., Rahman, M. M., & Moniruzzaman, M. (2019). Predictive modeling of hospital readmissions using metaheuristics and data mining. *Expert Systems with Applications*, 127, 170–186. https://doi.org/10.1016/j.eswa.2019.03.051

[3]LucienCastle. *Diabetes Patient Readmission Prediction*. GitHub repository. Available at: https://github.com/LucienCastle/diabetes-patient-readmission-prediction

[4]Laurenemilyto. *Predicting Hospital Readmission*. GitHub repository. Available at: https://github.com/laurenemilyto/predicting-hospital-readmission

Thank You