VaidyaHealth :
AI-Powered Application for Prediction of 30-Day Readmission Risk for Heart Failure Patients

Team Name : VaidyaCoders

Chosen Use Case: UC- 4

PROBLEM STATEMENT & MOTIVATION

Goal :

- Predict 30-day hospital readmission in heart failure (HF) patients to enable early intervention and reduce preventable readmissions.

Background:

- Nearly 1 in 4 heart failure patients in the United States are readmitted within 30 days of discharge.
- In Asian countries, 30-day readmission rates can be as high as 22%.
- By 2030, U.S. heart failure–related healthcare costs are expected to exceed $70 billion annually (NIH, 2022).

PROBLEM STATEMENT & MOTIVATION

Why This Matters:

- Increases the risk of death and worsens patient outcomes (morbidity and mortality).
- Causes significant financial burden on patients and their families.
- Adds pressure to already overwhelmed healthcare systems.

Motivation for Choosing Use Case 4:
Heart failure readmission is a globally relevant healthcare challenge. Predicting early readmissions using machine learning can support clinical decision-making, improve patient care, and optimize hospital resource allocation.

PROJECT OBJECTIVE

We aimed to develop an AI- Powered Application that can:

- Predict whether a patient will be readmitted within 30 days of hospital discharge after being treated for heart failure.

This is framed as a **binary classification problem**, where the target variable is defined as:

- **1 (Positive):** Patient is readmitted within 30 days
- **0 (Negative):** Patient is not readmitted within 30 days

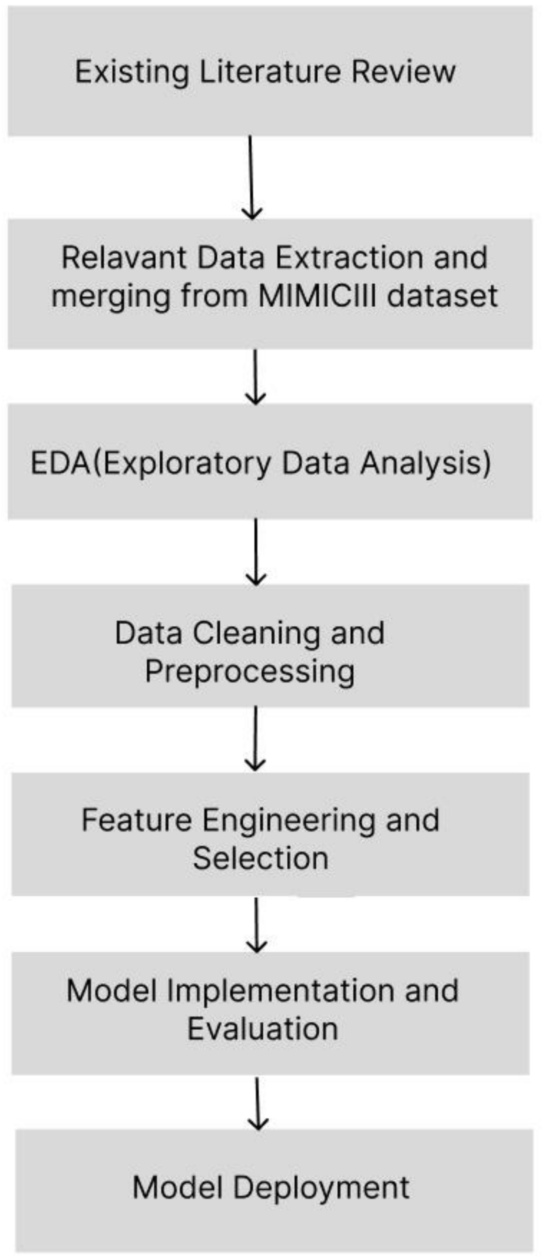
DATASET DESCRIPTION

- We worked with a subset of **8 tables** shared via OneDrive, sourced from the **MIMIC-III** dataset.
- **MIMIC-III** stands for: **Medical Information Mart for Intensive Care III** — a large, publicly available dataset consisting of de-identified health records of over 40,000 ICU patients from the Beth Israel Deaconess Medical Center (Boston, USA).
- **Reference – Official MIMIC-III Table Documentation:** https://mimic.mit.edu/docs/iii/tables/

OUR APPROACH

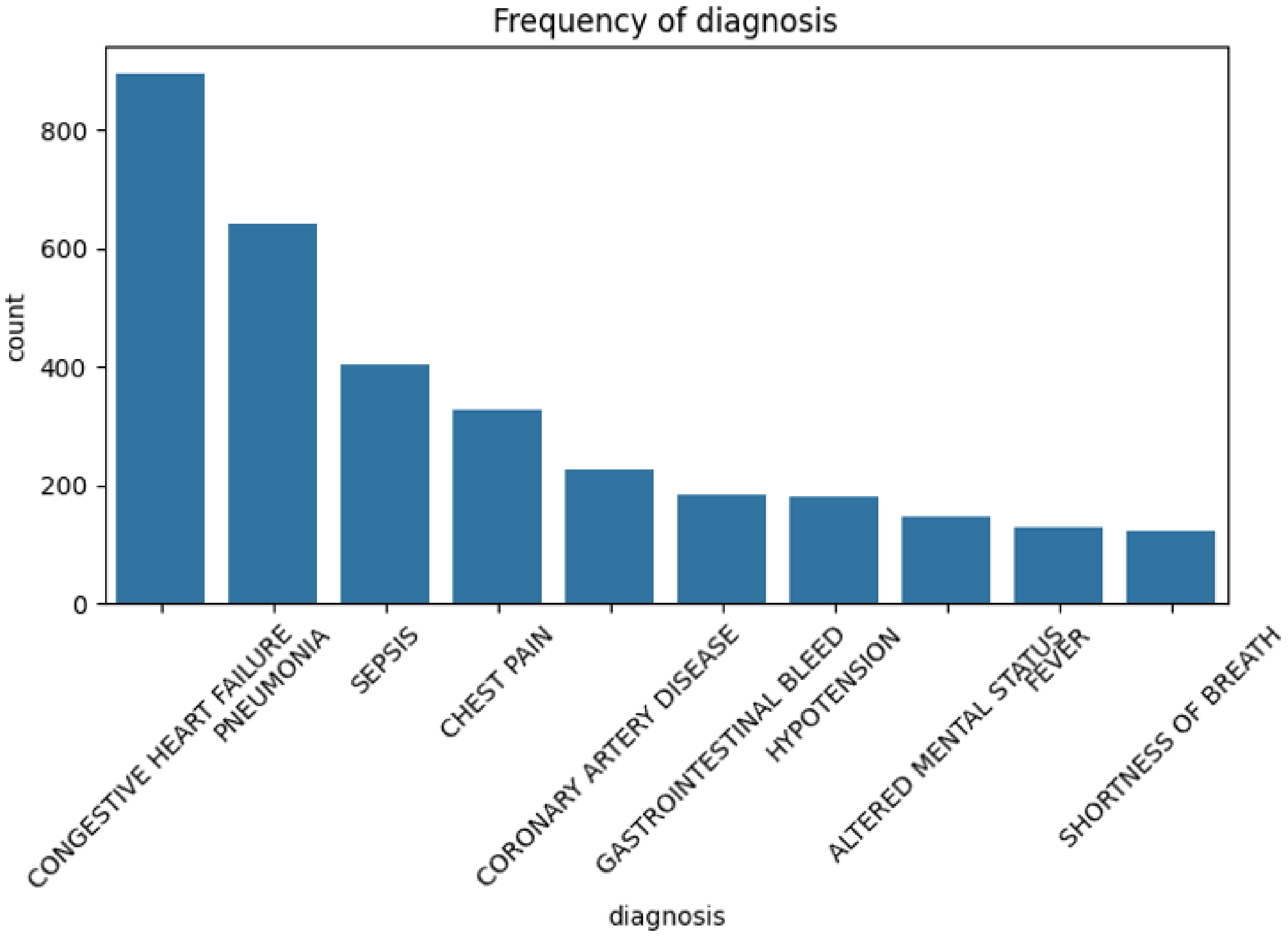
Our approach can be understood through the workflow diagram on the side.

- **Clinically grounded**: Informed by medical research and real-world readmission risk factors.
- **Data-efficient**: Built under tight time and feature constraints.
- **Handled class imbalance** (SMOTE, threshold tuning)
- **Trained multiple models** (XGBoost, LightGBM, etc.)
- **Recall-first strategy**: Prioritized catching true readmissions to ensure patient safety.



EXPLORATORY DATA ANALYSIS

- Total Heart Failure Admissions: 14,040 patients recorded
- Age Distribution: 0-110 (avg: 72)



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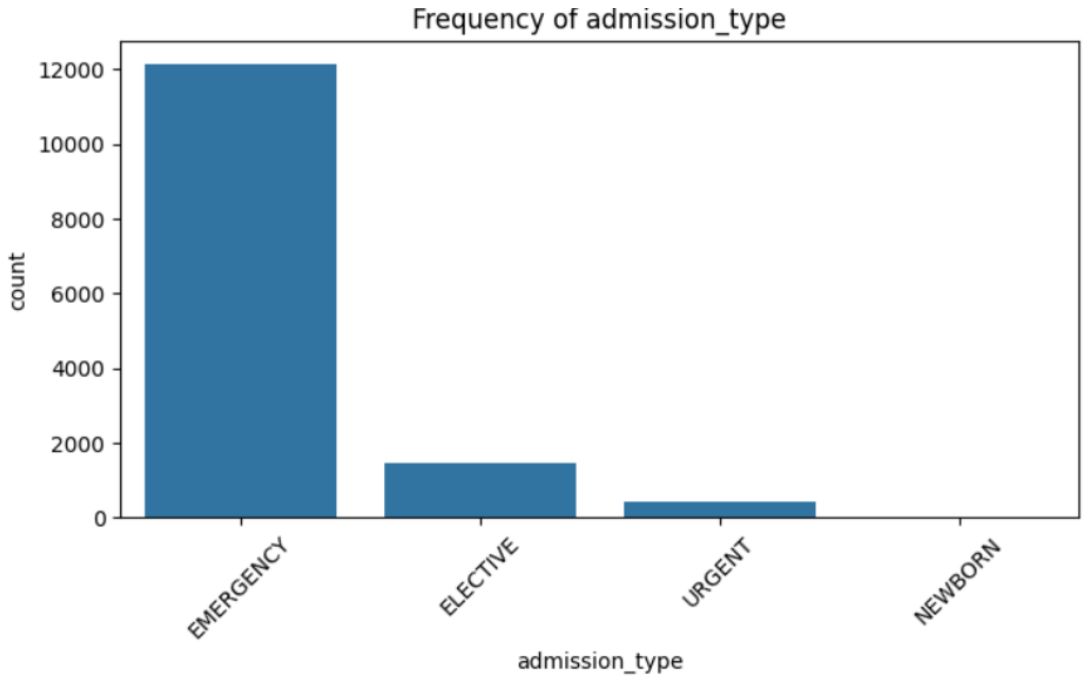
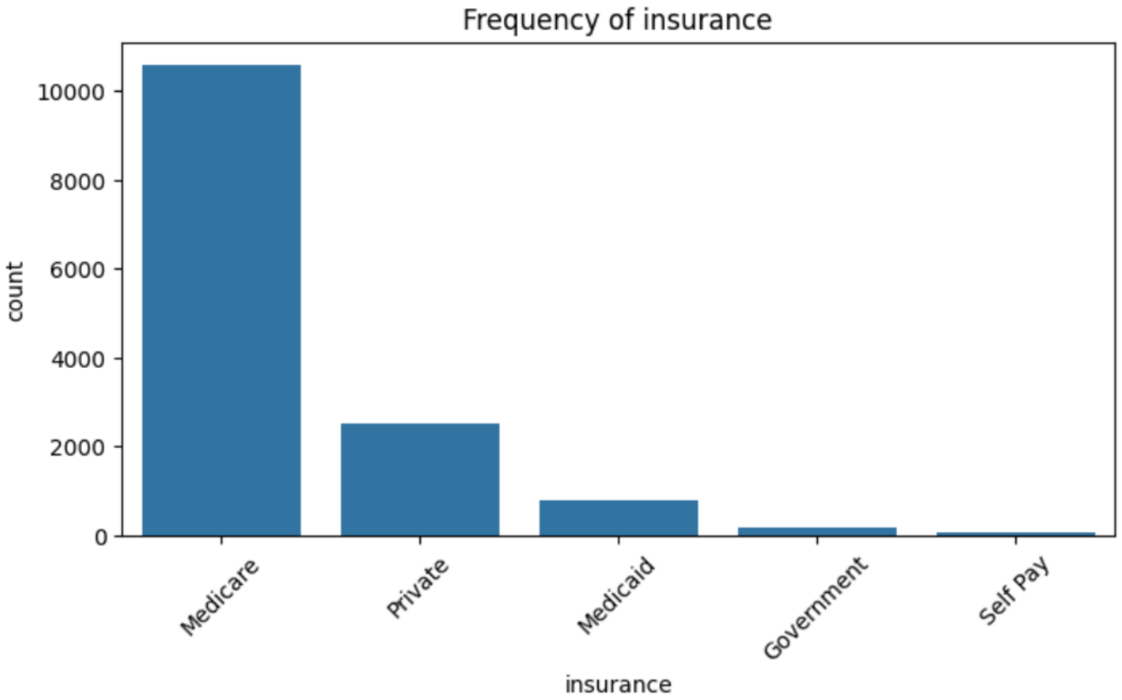
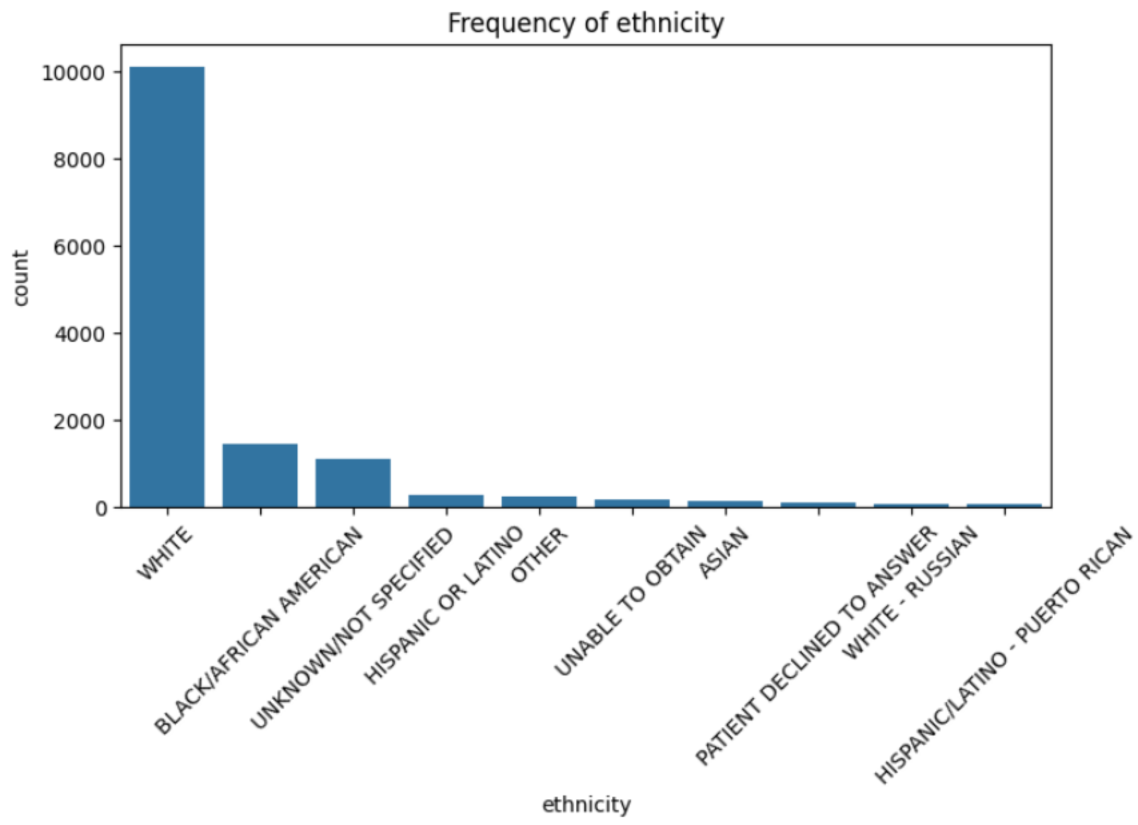
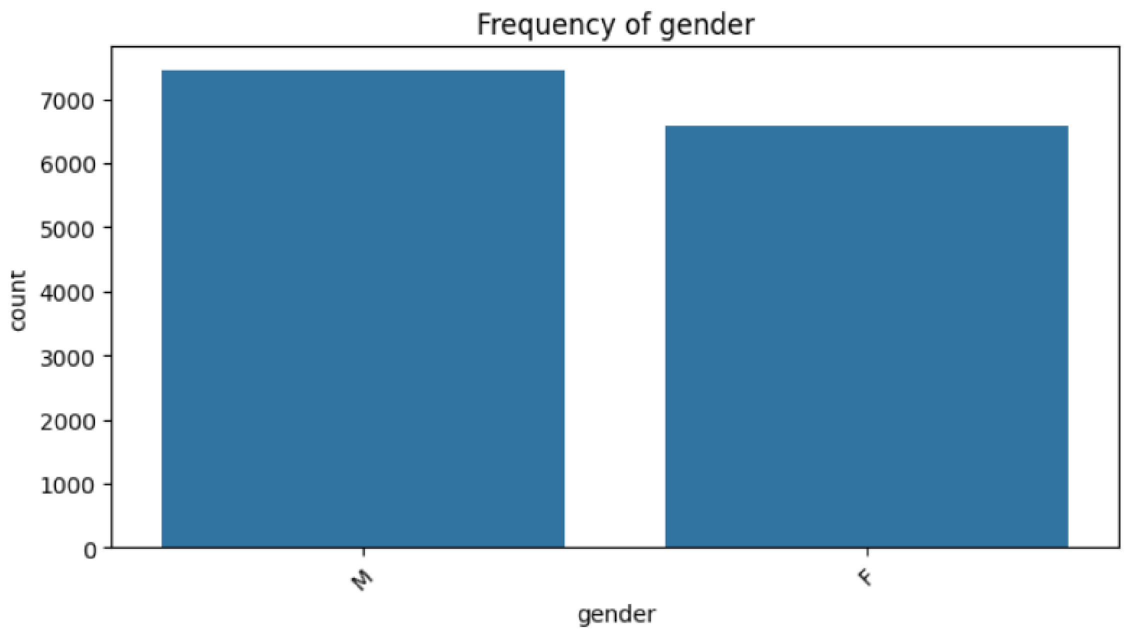




EXPLORATORY DATA ANALYSIS





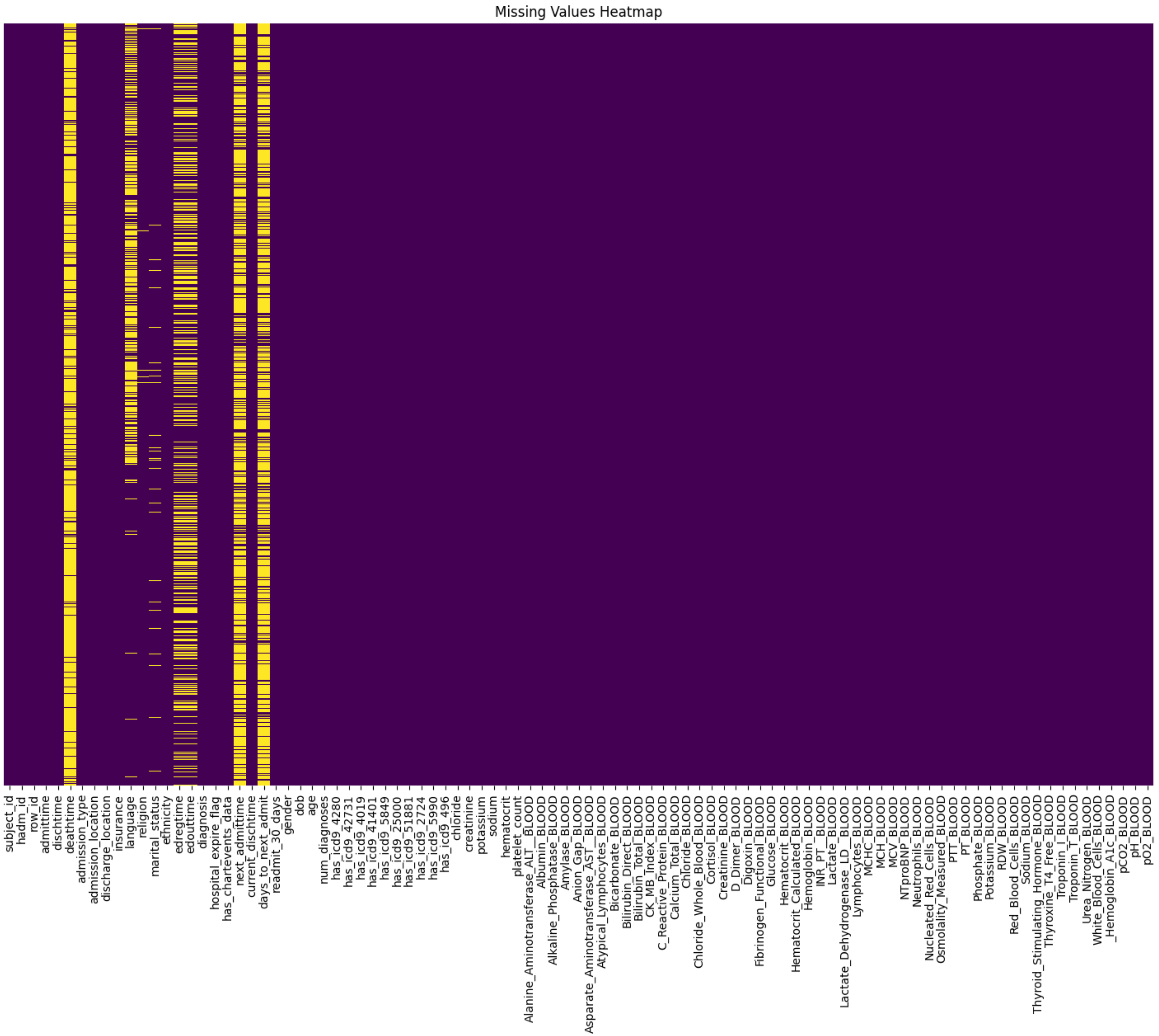
DATA CLEANING & PREPROCESSING

HANDLING OF NULL VALUES :

•**Dropped features** with more than **60% missing values**, as they provided limited usable information.

•For remaining features with missing data, applied appropriate **imputation strategies** based on data type and distribution:

- **Mean** for normally distributed numerical features
- **Median** for skewed numerical features
- **Mode** for categorical features



ENCODING CATEGORICAL VARIABLES :

- Converted categorical features into numerical format using **Label Encoding**, ensuring compatibility with machine learning models.

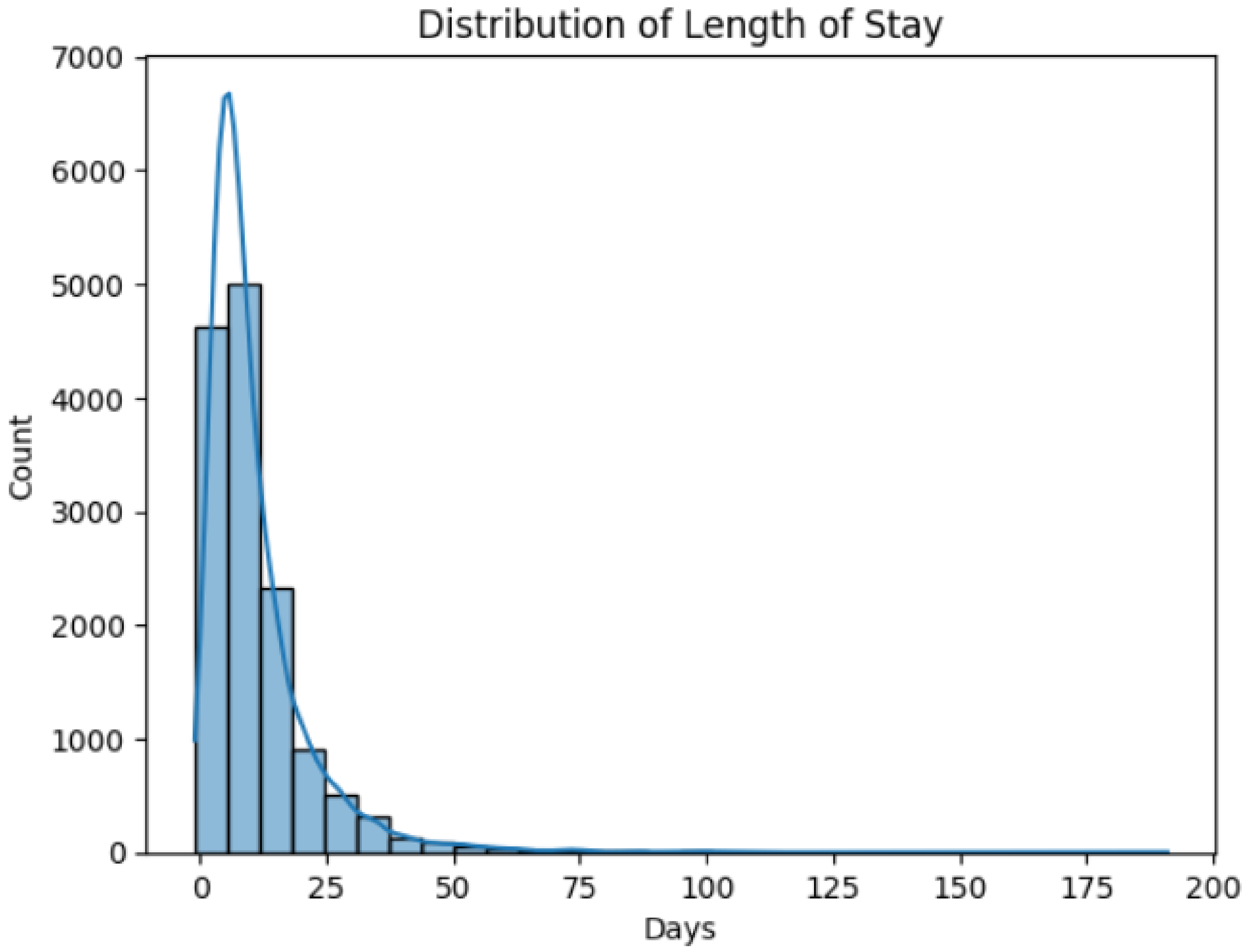
In [80]:

```
from sklearn.preprocessing import LabelEncoder

categorical_cols = hf_model_data.select_dtypes(include='object').columns

le = LabelEncoder()
for col in categorical_cols:
    hf_model_data[col] = le.fit_transform(hf_model_data[col].astype(str))
```

FEATURE ENGINEERING & SELECTION

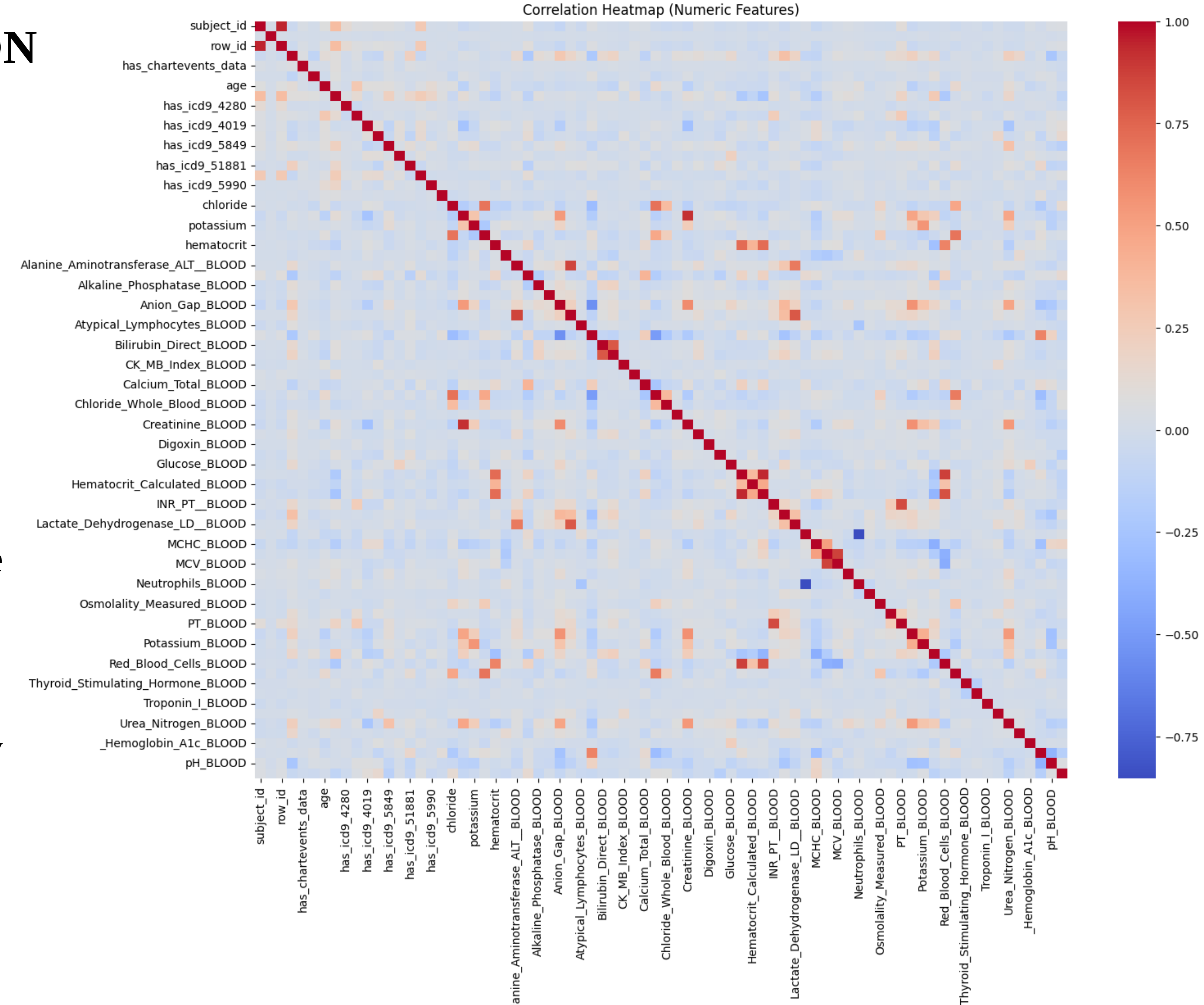
DATA LEAKAGE HANDLING & NEW FEATURE CREATION :

- **Prevented data leakage** by removing features that could reveal future information (e.g., **Discharge Location**).
- **Engineered new features** such as **Length of Stay (LOS)** to enrich the dataset with meaningful clinical insights.



FEATURE CORRELATION ANALYSIS :

- Generated a **correlation heatmap** to identify relationships between numerical features.
- Used this to detect **highly correlated (redundant) features**, reduce multicollinearity, and enhance model stability.
- Helped in making informed decisions during **feature selection and dimensionality reduction**.

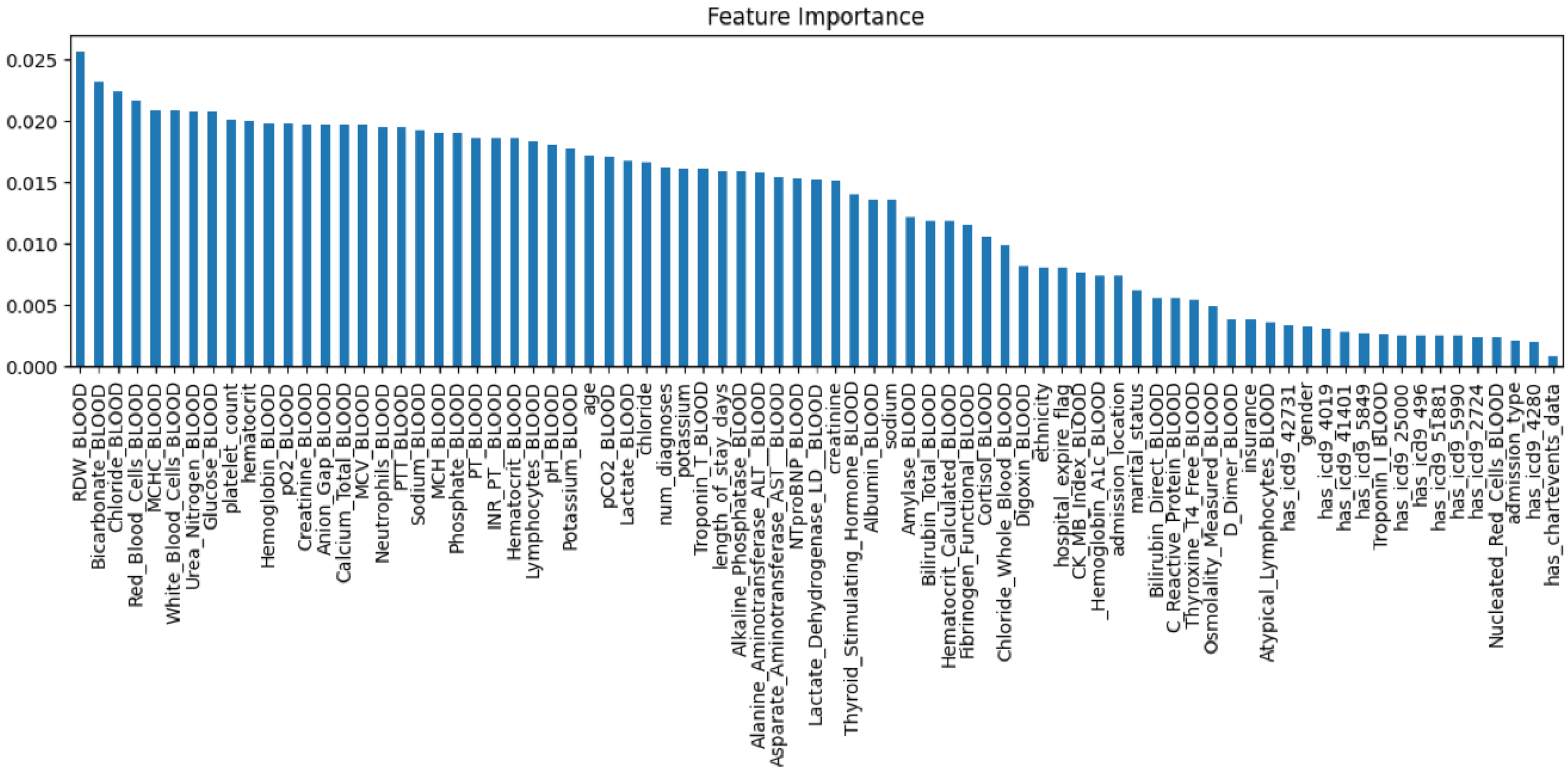


FEATURE SELECTION

- Conducted an **extensive literature review** to identify **80 clinically relevant features** commonly used in readmission prediction studies.
- Used a **Random Forest Classifier** to **rank features based on importance scores**.
- Selected the **top 20 features** by combining insights from both **research evidence** and **model-based feature importance**.
- These features were used as the final input set for model implementation.

```python
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier

X = hf_model_data.drop(columns=['readmit_30_days'])
y = hf_model_data['readmit_30_days']

rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X, y)

# Get importance
importances = pd.Series(rf.feature_importances_, index=X.columns)
importances.sort_values(ascending=False).plot(kind='bar', figsize=(12, 6), title="Feature Importance")
plt.tight_layout()
plt.show()
```

FEATURE ENGINEERING & SELECTION



EVALUATION METRICS

In a highly imbalanced healthcare dataset like ours, **traditional accuracy can be misleading**. To evaluate our model more effectively, we focused on metrics that reflect performance on the minority class (readmitted patients):

1. <u>Recall (Sensitivity)</u>

- Measures the proportion of actual readmissions that our model correctly identified.
- **Why important?** In healthcare, missing a true readmission can lead to serious consequences — high recall ensures we capture as many at-risk patients as possible.

2. <u>PR-AUC (Precision-Recall Area Under Curve)</u>

- Measures how well the model balances precision and recall across different thresholds.
- **Why important?** Unlike ROC-AUC, which can be inflated by class imbalance, **PR-AUC focuses specifically on the minority class**, making it a more meaningful metric in our case.

EVALUATION METRICS

3. <u>F1-Score</u>

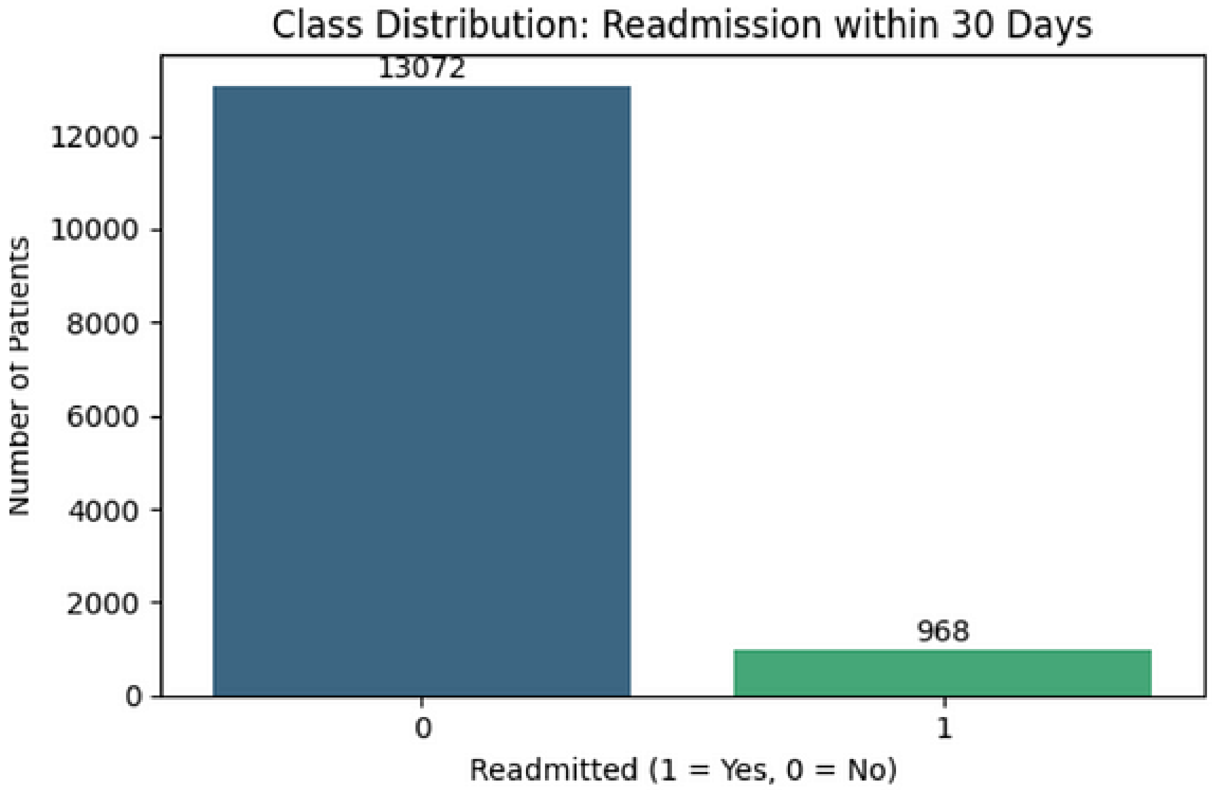
- The harmonic mean of precision and recall.
- **Why important?** It balances the trade-off between false positives and false negatives, especially useful when one class is much smaller than the other.

We prioritized **Recall and PR-AUC** to ensure clinical safety (don’t miss at-risk patients), while also monitoring **Precision and F1-Score** to assess practical usability and false alarm rates.

THE 5 KEY CHALLENGES

CHALLENGE 1 - **Severe Class Imbalance**

- Our dataset had a major imbalance: out of 14,670 records, only 968 (6.6%) were positive cases (patients readmitted within 30 days), while 13,702 (93.4%) were negative cases (not readmitted). This skew caused models to default to predicting the majority class, inflating accuracy but failing to correctly identify readmissions.



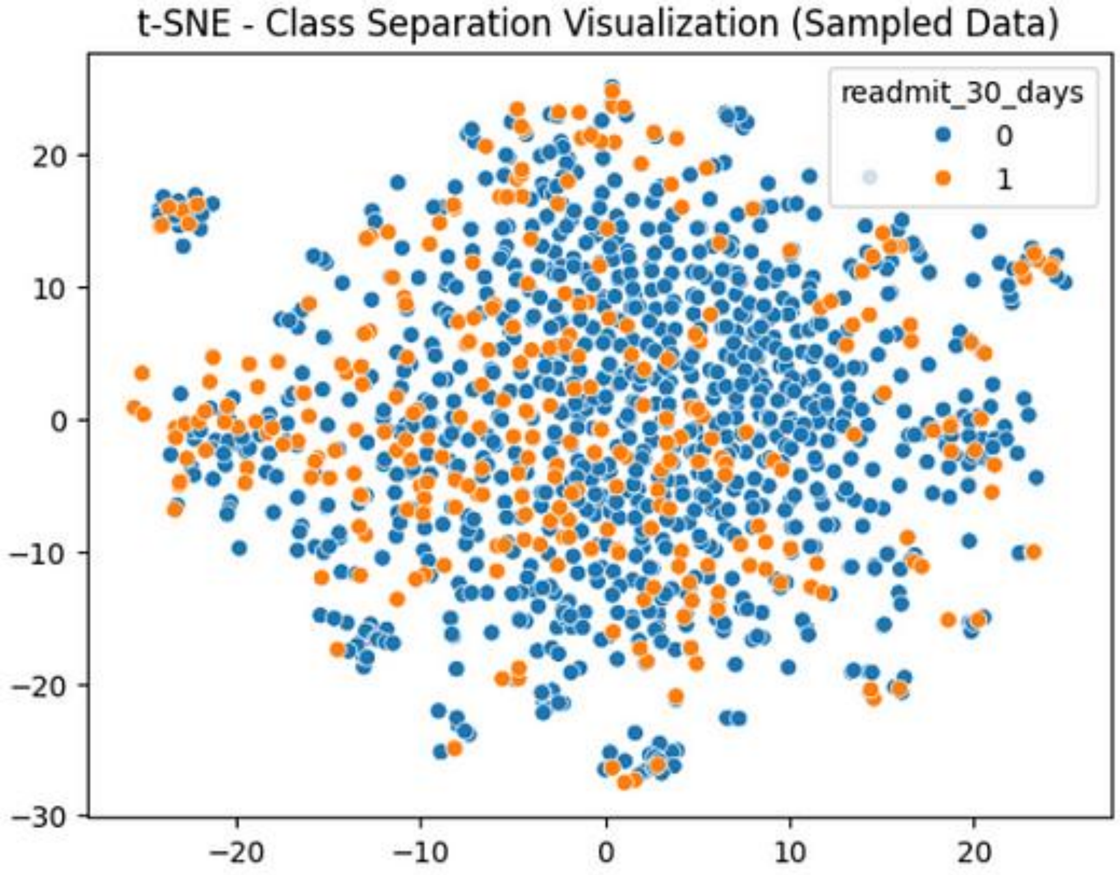
CHALLENGE 2 - **Limited and Constrained Feature Set**

- Critical clinical features like Heart Rate (HR), Systolic & Diastolic Blood Pressure (SBP/DBP), and Mean Arterial Pressure (MAP), usually recorded in the first 24 hours of ICU admission, were missing. These vital signs, often requiring extensive cleaning and normalization, could not be incorporated due to our tight 3-day timeline, limiting our ability to benchmark against existing studies.

Variable	Description	MIMIC-III Table
Heart rate (HR)	Beats per minute	CHARTEVENTS
Systolic blood pressure (SBP)	Systolic BP	CHARTEVENTS
Diastolic blood pressure (DBP)	Diastolic BP	CHARTEVENTS
Mean blood pressure	Mean arterial pressure	CHARTEVENTS
Respiratory rate	Breaths per minute	CHARTEVENTS
Body temperature	Temperature	CHARTEVENTS
Saturation pulse oxygen (SpO2)	Oxygen saturation (%)	CHARTEVENTS
Urine output (first 24 hours)	Volume output in first 24 hrs	OUTPUTEVENTS

CHALLENGE 3: **Poor Class Separability in Feature Space**

- Even after applying dimensionality reduction techniques like PCA, t-SNE and LDA there was significant overlap between the two classes, indicating that the available features lacked strong discriminatory power. This made it difficult for models to learn meaningful decision boundaries, especially for the minority class.



CHALLENGE 4 - **Sampling Techniques Failed Us**

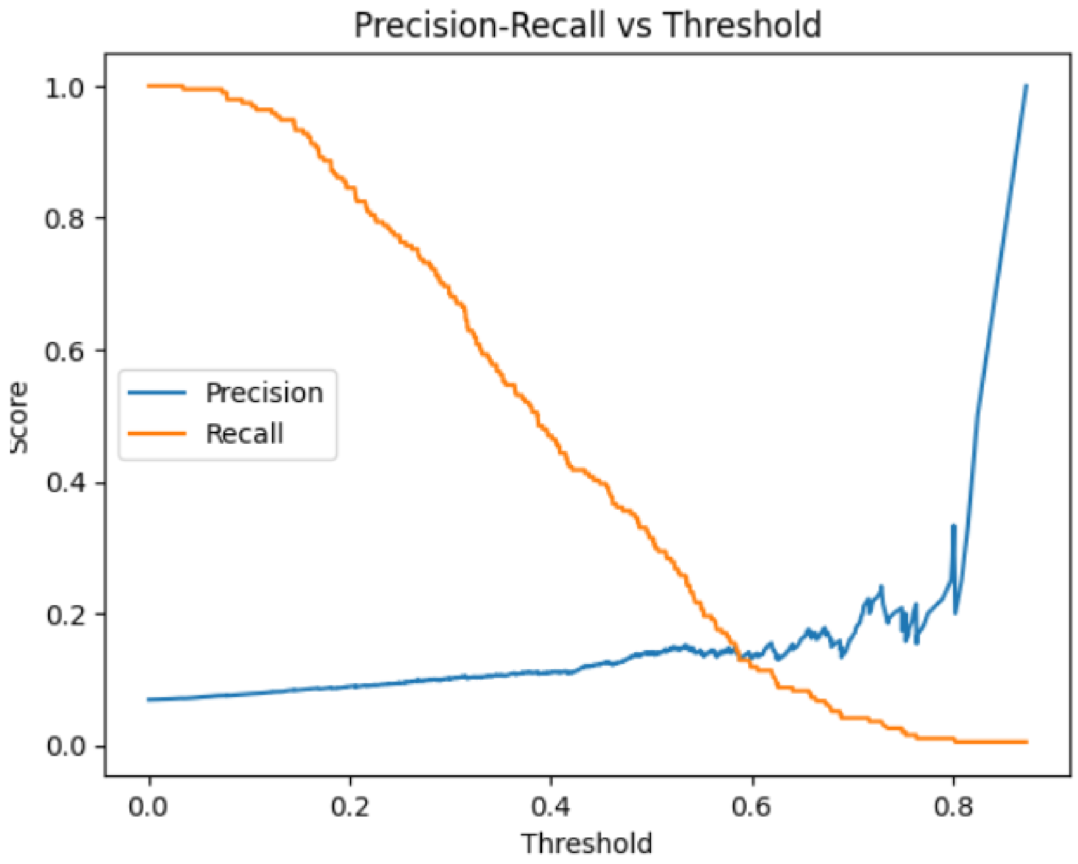
- We experimented with numerous class balancing methods — Random Oversampling, Random Undersampling, SMOTE, SMOTEENN, BorderlineSMOTE etc among others. Unfortunately, none improved the detection of positive cases without sacrificing performance on the majority class. Metrics for class 0 remained above 90%, while class 1 suffered from low precision, accuracy, and F1-scores.

```
print("2. RF trained on SMOTEENN resampled data")
evaluate_model(rf_smoteenn, X_test, y_test)
```

```
2. RF trained on SMOTEENN resampled data
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.87      0.90      2614
           1       0.12      0.25      0.16       194

    accuracy                           0.82      2808
   macro avg       0.53      0.56      0.53      2808
weighted avg       0.88      0.82      0.85      2808

Confusion Matrix:
 [[2264  350]
 [ 146   48]]
AUROC Score: 0.6478507875910047
PR-AUC Score: 0.10388736787737063
```

CHALLENGE 5 : **Precision-Recall Trade-Off**

- Lastly, one of the most subtle but critical challenges was **balancing precision and recall**. In healthcare, especially for high-risk predictions like hospital readmissions, missing a true positive (low recall) can be dangerous, but over-predicting readmissions (low precision) can lead to false alarms and wasted resources. We spent significant time adjusting thresholds, tuning hyperparameters, and analyzing ROC/PR curves to find a “sweet spot” that maintained a clinically acceptable balance between these two competing metrics ensuring practicality.

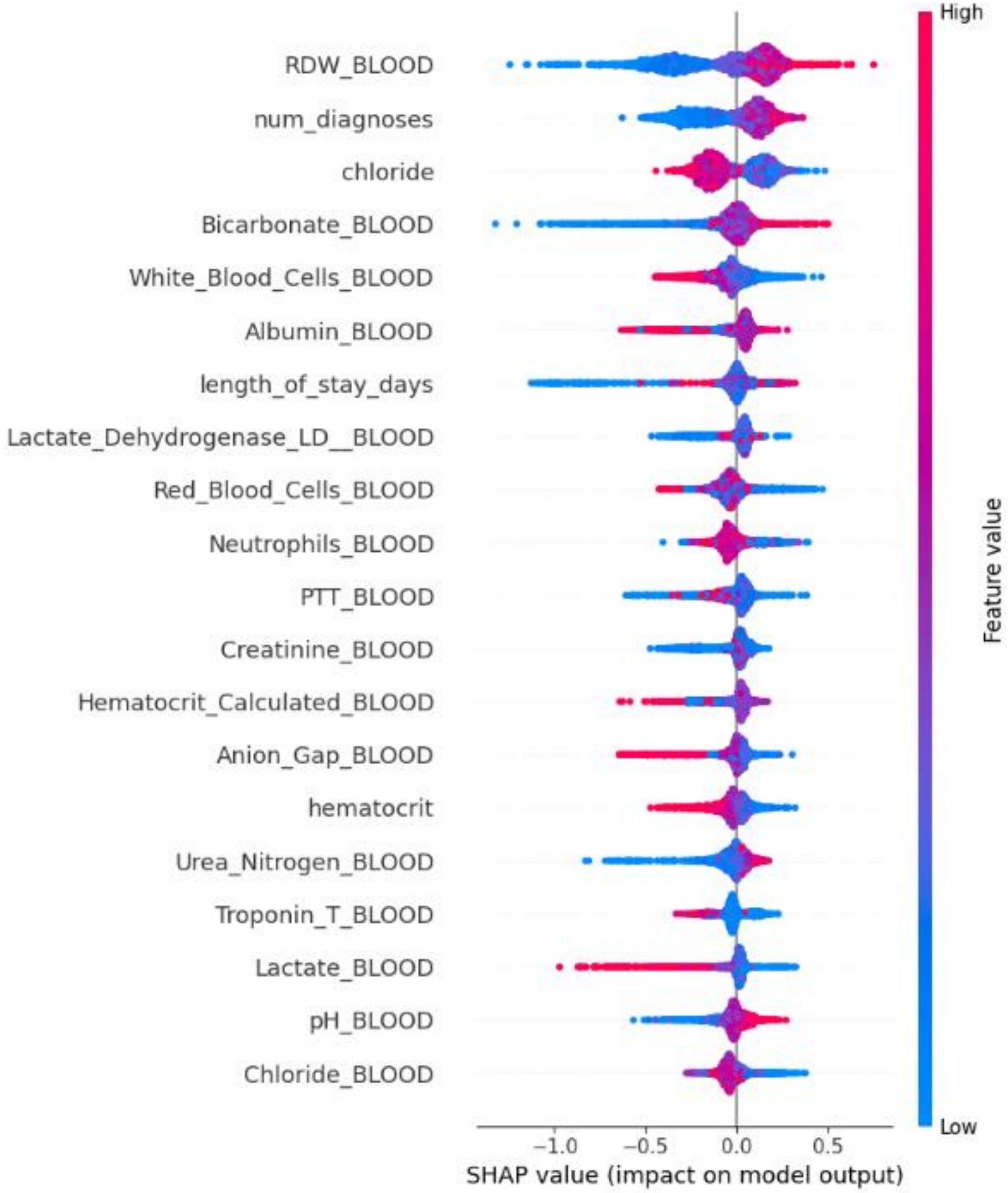


MODEL PERFORMANCE

Model / Sampling Technique	Recall (Class 1)	F1 Score	PR-AUC
Random Forest (baseline)	0.18	0.22	0.102
Balanced Random Forest	0.31	0.2	0.116
XGBoost (scale_pos_weight=13.51)	0.31	0.18	-
XGBoost (Threshold = 0.2)	0.85	0.16	0.122
XGBoost + BorderlineSMOTE	0.58	0.19	0.112
LightGBM (original, Threshold=0.2)	0.91	0.16	0.122
LightGBM + SMOTE	0.52	0.18	0.117
Logistic Regression (Threshold=0.1)	1	0.13	0.122
Stacking (XGB+RF+GB + LR meta)	0.01	0.02	-
EasyEnsembleClassifier	0.66	0.18	0.12

MODEL INTERPRETABILITY (SHAP ANALYSIS)

- SHAP (SHapley Additive exPlanations) analysis is a method for explaining the output of any machine learning model by quantifying the contribution of each input feature to a prediction.
- Helps build trust in predictions and identify clinically meaningful features.



LIMITATIONS & CONSTRAINTS

Our model achieves **very high recall (~91%)** but suffers from **low precision (~12-15%)**.

- **Recall:** Of all patients who were actually readmitted within 30 days, how many did our model correctly identify?
- **Precision:** Of all patients predicted to be readmitted, how many truly were readmitted?

This means our model is strong at catching almost all true readmissions but also produces many false positives.

This is **not a drawback but a deliberate trade-off**, considering the healthcare context where missing a readmission can be more dangerous than a false alarm.

SOLUTIONS & REASONS BEHIND LIMITATION

1. Limited & Constrained Feature Set

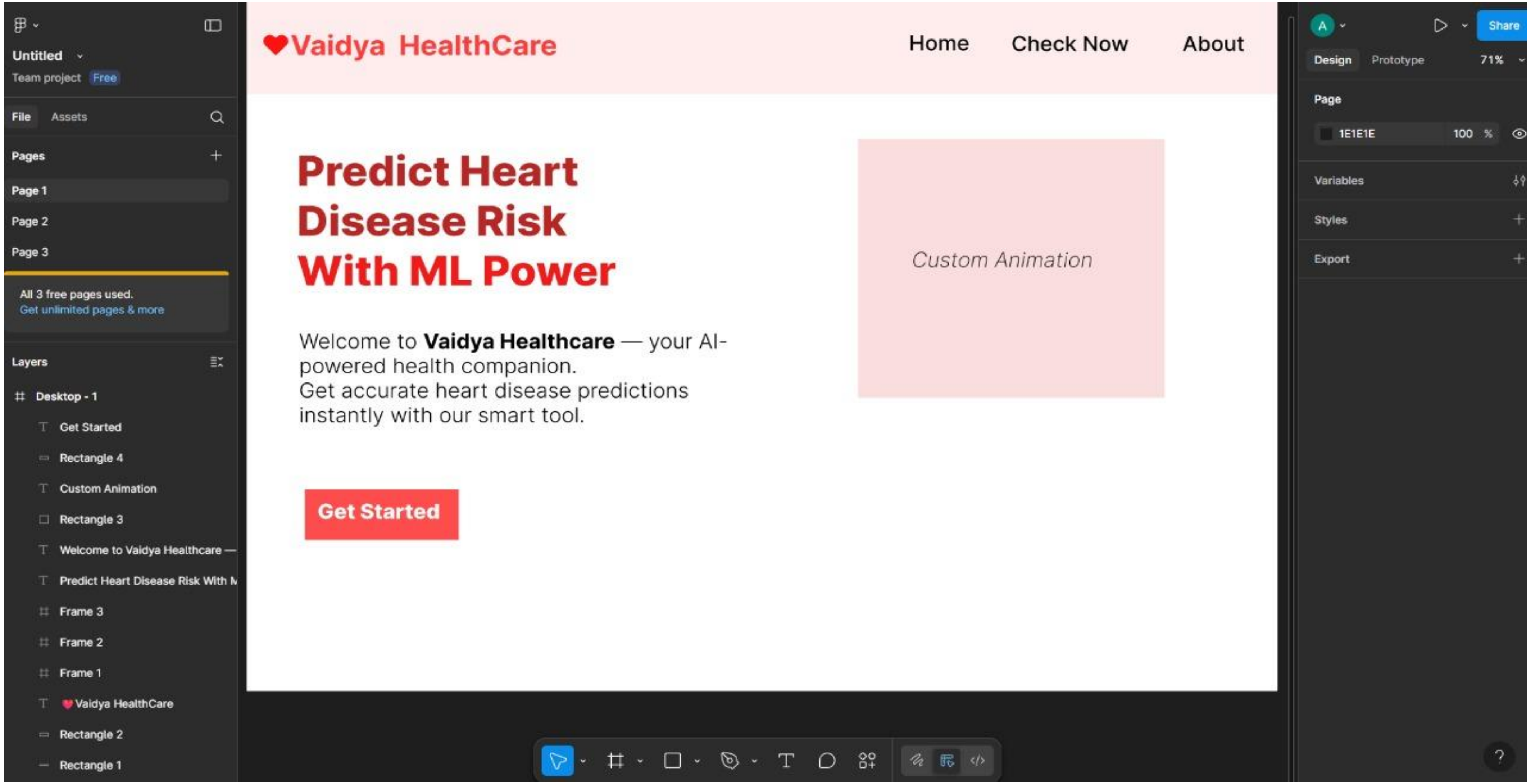
- Critical clinical features like **Heart Rate (HR), Systolic & Diastolic Blood Pressure (SBP/DBP), Mean Arterial Pressure (MAP)** — usually recorded within 24 hours of ICU admission — were missing from our dataset (Present in Original MIMIC-III Dataset).
- These features are important for precise predictions and are commonly used in similar medical research to improve both recall and precision (based on our existing literature review).
- Due to their absence, our model had to rely on fewer and less informative features, which limited precision.

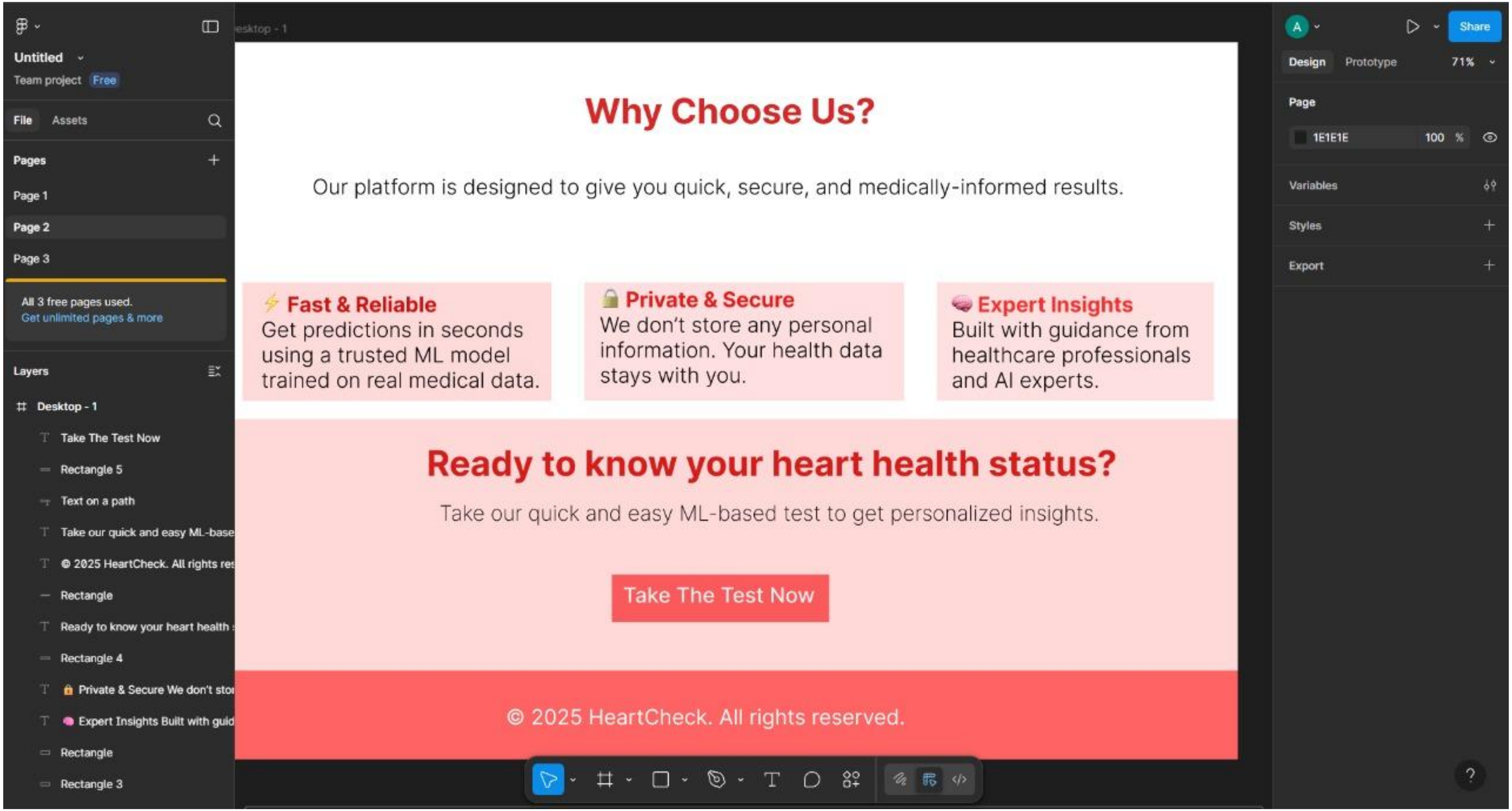
2. Time Constraint Impacting Feature Engineering

- With only **3 days** for the hackathon, our priority was to build a **robust pipeline focusing on capturing as many readmissions as possible**, resulting in high recall.
- This limited the time available for deeper feature engineering, advanced data cleaning, and precision-focused tuning.
- Given more time, we would explore domain-specific features and methods to reduce false positives and improve precision.

MODEL INTEGRATION

FIGMA DESIGNS





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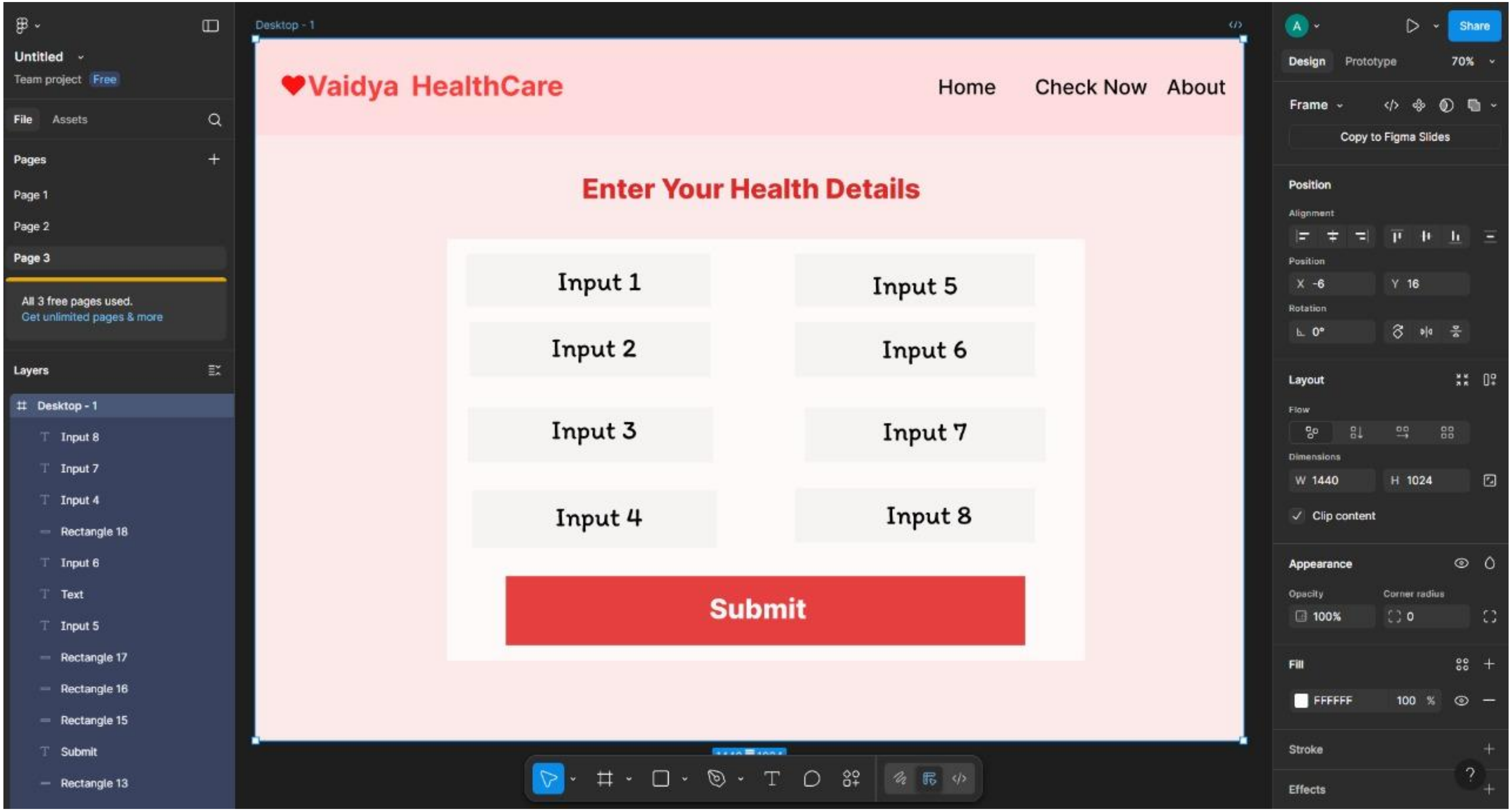
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HOME PAGE

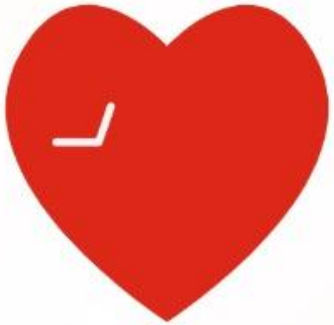
VaidyaHealth

Home Check Now About

Predict 30-Day Heart Failure Readmission
with the Power of Machine Learning

Welcome to **VaidyaHealth** — your AI-powered health companion. Get fast, reliable predictions on the risk of hospital readmission within 30 days for heart failure patients. Empower smarter care decisions with intelligent insights.

Get Started



Why Choose Us?

Our platform is designed to give you quick, secure, and medically-informed results.

ABOUT PAGE

VaidyaHealth

Home Check Now About

About VaidyaHealth

"VaidyaHealth" is an intelligent, machine learning–powered tool designed to predict the risk of hospital readmission within 30 days for heart failure patients. Developed by *Team VaidyaCoders* (Pragya Tripathi, Nakul Jain, Akshit, Priyanshu), it empowers clinicians and patients to make proactive, data-driven decisions aimed at improving recovery outcomes and reducing avoidable readmissions.

Our Mission

To reduce preventable hospital readmissions by enabling early risk detection, providing healthcare providers and patients with actionable insights that improve post-discharge care and patient wellbeing.

How It Works

Our ML model analyzes key clinical and demographic features, including:

- Patient age and length of hospital stay
- Common diagnosis codes (ICD-9) related to heart failure and comorbidities
- Laboratory Results of over 50 lab values and vital signs
- Clinical History (length of hospital stay, number of prior diagnoses etc)

Data Privacy

VaidyaHealth processes patient data only during prediction and does *not* store, share, or retain any personal information. Ensuring your privacy and data security is our utmost priority.

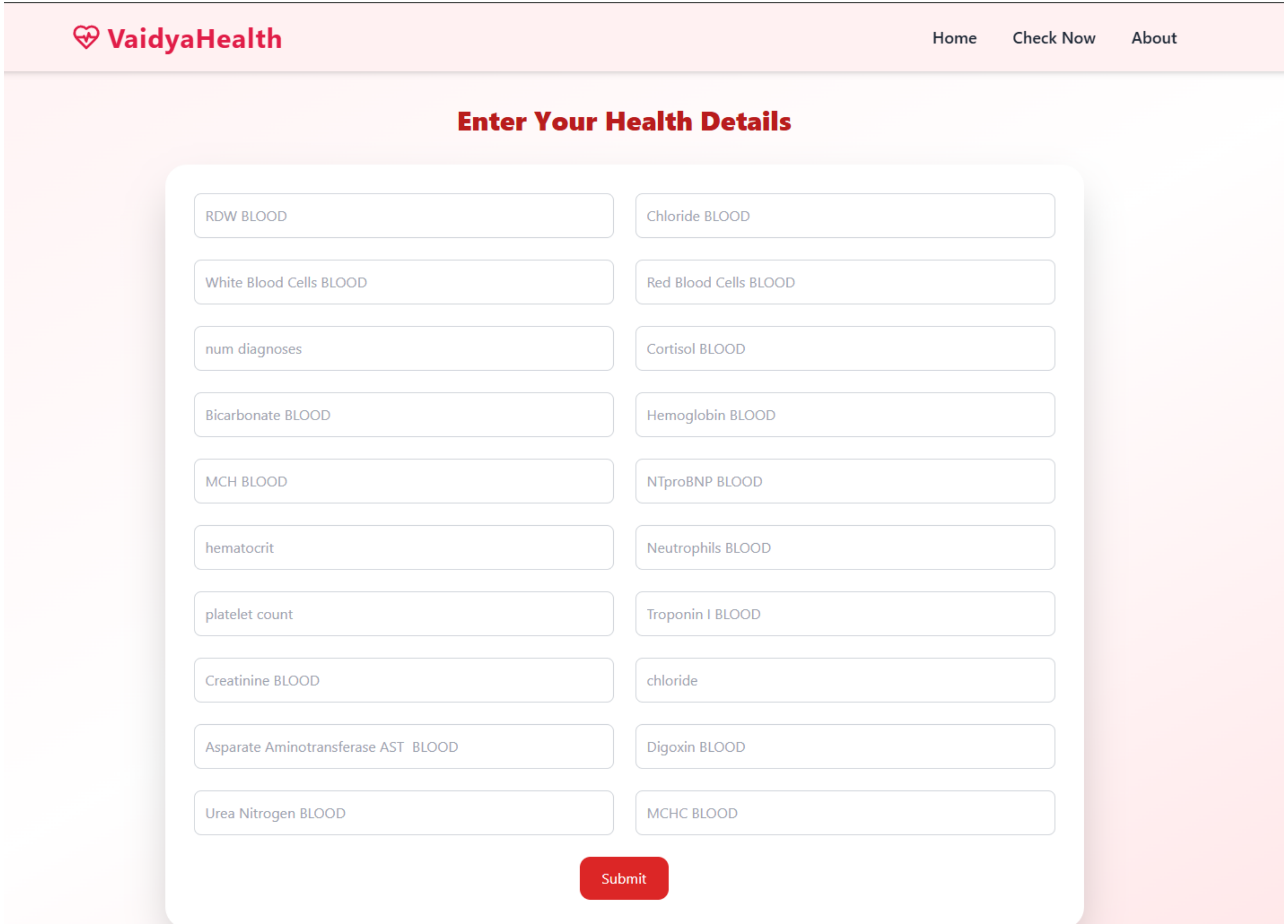
Built By

Developed by *Team VaidyaCoders* — Pragya Tripathi, Nakul Jain, Akshit, and Priyanshu — passionate about applying technology to solve real-world healthcare challenges.

Disclaimer

This tool is intended solely for educational and preliminary screening purposes. It is *not* a substitute for professional medical advice, diagnosis, or treatment. Always consult qualified healthcare professionals for any medical concerns.

FORM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Chloride BLOOD
White Blood Cells BLOOD
Red Blood Cells BLOOD
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Cortisol BLOOD
Bicarbonate BLOOD
Hemoglobin BLOOD
MCH BLOOD
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Neutrophils BLOOD
platelet count
Troponin I BLOOD
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Urea Nitrogen BLOOD
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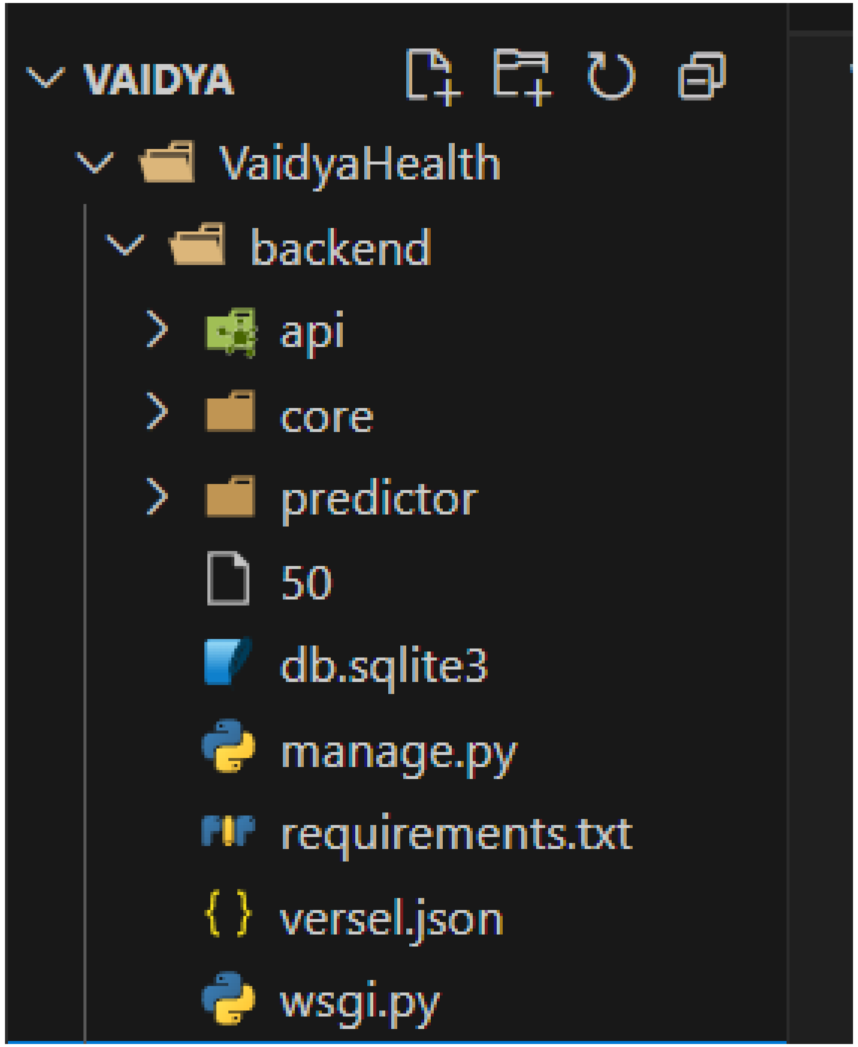
BACKEND INTEGRATION



BACKEND FOLDERS

📁 `backend/`

- The main Django project directory.

📁 `api/`

- Handles all API-related operations.
- contains `urls.py`

📁 `core/`

- Contains core functionalities like `models.py`, settings.py

📁 `predictor/`

- Module for machine learning or AI-based predictions.
- Contains View.py and model joblib file

BACKEND FLOW

- Built using **Django (Python Web Framework)**.
- Handles API requests from the **frontend**.
- Structured for modularity: API handling, core logic, and ML prediction are separated.

•Frontend file `Form.jsx` sends HTTP requests (likely using Axios or Fetch).
•Requests hit the Django backend **API endpoint**.
•**CORS headers** are enabled to allow cross-origin requests from frontend to backend.
•Example flow:

```
Form.jsx → /api/predict → Backend processes → Response returned
```

TECH STACK USED

FUTURE SCOPE

- Incorporate more clinical features such as vital signs (HR, BP, MAP) and lab results from the first 24 hours of ICU admission for improved precision.

- Deploy the model in a real-world hospital setting to provide early alerts for at-risk patients and reduce readmission rates.

- Integrate temporal data and explore time-series models like LSTM to better capture patient history and progression.

THANK YOU