

Hospital Readmission Prediction (30-Day Readmission Risk)

Machine Learning project that predicts whether a patient will be **readmitted within 30 days** after hospital discharge.

This system provides an **early warning risk score** to help hospitals improve patient safety, reduce costs, and optimize capacity.

Project Objective

Hospital readmissions within 30 days are a major problem for the healthcare system:

- Increased hospital costs
- Overload on doctors and nurses
- High risk for chronic and elderly patients
- Negative impact on hospital quality metrics (Readmission Rate)

This project aims to build a **predictive model** that identifies high-risk patients *before* discharge, enabling preventive interventions.

Problem Description

Predicting readmission risk is extremely challenging for clinicians because:

- Patient medical history is complex
- Chronic diseases vary widely
- Home recovery can't be monitored
- Social & environmental factors affect outcomes

A data-driven ML model can support decision-making by providing **objective risk predictions**.

Success Metrics

The model performance was evaluated using:

- **ROC-AUC ≥ 0.70**
 - **PR-AUC** (ideal for imbalanced datasets)
 - Minimizing **false negatives**
 - Balanced performance after SMOTE
 - SHAP interpretability for explainable AI
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Dataset

Source: UCI Machine Learning Repository — Diabetic Hospital Readmission Dataset

Size: ~100,000 patient records

Key features include:

- Age group
- Gender
- Number of previous inpatient visits
- Emergency visits
- Number of laboratory procedures
- Number of medications
- Insurance & discharge type
- **Target:** readmitted (NO, >30, <30)

The target was converted to a **binary classification**:

- **1:** Readmitted within 30 days
- **0:** Not readmitted

Technical Approach

1 Data Preparation & EDA

- Missing value treatment
- Outlier handling (IQR & winsorization)
- Correlation analysis
- Categorical encoding
- Feature engineering

2 Imbalanced Data Solution

Dataset distribution:

- **11% positive (readmitted)**
- **89% negative**

Solution: **SMOTE Oversampling**

3 Modeling

Main model: **XGBoost Classifier**

Best performance:

- **ROC-AUC: 0.74**

- **PR-AUC: 0.32**

Explainable AI (SHAP)

Used SHAP to explain model outputs:

- SHAP Summary Plot
- Feature Importance
- Doctor-friendly interpretation

This creates a transparent, trustworthy model.


FastAPI Service (Backend)

The trained ML model is served via a REST API built with **FastAPI**.

Run API:

```
uvicorn app:app --reload
```

Swagger documentation:

 <http://127.0.0.1:8000/docs>

Streamlit User Interface

A clean and user-friendly web interface for hospital staff to enter patient details and obtain risk predictions.

Run Streamlit:

```
streamlit run ui.py
```

Project Structure

```
project/
```

```
|
```

```
|— data/
```

```
|   └─ diabetic_data.csv
```

```
|
```

```
|— models/
```

```
|   └─ readmission_xgb.pkl
```

```
|
```

```
|— app.py
```

```
└─ main.py
└─ ui.py
└─ shap_summary.png
└─ README.md
```

Installation

1. Create a virtual environment

```
python -m venv .venv
```

2. Activate environment

```
.venv\Scripts\activate
```

3. Install dependencies

```
pip install -r requirements.txt
```

Challenges & Solutions

Challenge	Solution
Many missing values	Median imputation & dropping invalid rows
Highly imbalanced dataset	SMOTE oversampling
Numerous categorical features	One-hot & target encoding
Need for interpretability	SHAP explainability
API + UI deployment	FastAPI + Streamlit integration

Conclusion

This project provides a **complete early warning decision support system** for healthcare. It allows hospitals to:

- Identify high-risk patients
- Reduce readmission rates
- Improve quality metrics
- Enhance patient safety

With ML, API, UI, and explainability integrated end-to-end, this system can easily be extended for real-world use.

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