USING MACHINE LEARNING TO REDUCE HOSPITAL READMISSIONS

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OUTLINE

1. Introduction
2. Project Goals
3. Data
4. Methods and Models
5. Results
6. Value and Application
7. Conclusion

THE PROBLEM OF HOSPITAL READMISSIONS FOR DIABETES PATIENTS

- Hospital readmissions **within 30 days of discharge** are a common problem, particularly for patients with chronic conditions such as diabetes

- Hospital readmissions…
  - Negatively impact patient outcomes
  - **Increase healthcare costs**
  - Strain healthcare system capacity

- In response to this problem, Medicare established the Hospital Readmissions Reduction Program (HRRP), which financially penalizes hospitals with higher-than-expected rates of readmissions

A SOLUTION USING MACHINE LEARNING

- Machine learning models can **identify patients who are at risk** for 30-day readmissions
- **Key features and patterns** used by the model can inform treatment plans, reducing the likelihood of readmissions
- **Real-time** use of the model can **predict the probability** of a patient's readmission and enable providers to modify treatment plans dynamically

PROJECT GOALS

1. **Develop** a machine learning model to predict <30-day readmission based on patient treatment and discharge data
2. **Identify** key patient and treatment features that are most predictive of readmissions
3. **Provide recommendations** to help reduce the number of preventable readmissions

DATA

OVERVIEW

- Source
  - **University of California - Irvine, Machine Learning Repository**
    - "Diabetes 130-US hospitals for years 1999-2008"
- Represents **10 years** of clinical care at **130 US hospitals** and integrated delivery networks
- It includes **101,766 instances** with over **50 features** such as...
  - **Demographic** Information
  - **Health History** Information
  - **Admission** Information
  - **Treatment** Information
  - **Discharge** Information

DEFINING OUR TARGET VARIABLE

- The dataset contains three classes for readmission:
  - NO: Not readmitted
  - >30: Readmitted more than 30 days later
  - <30: Readmitted within 30 days

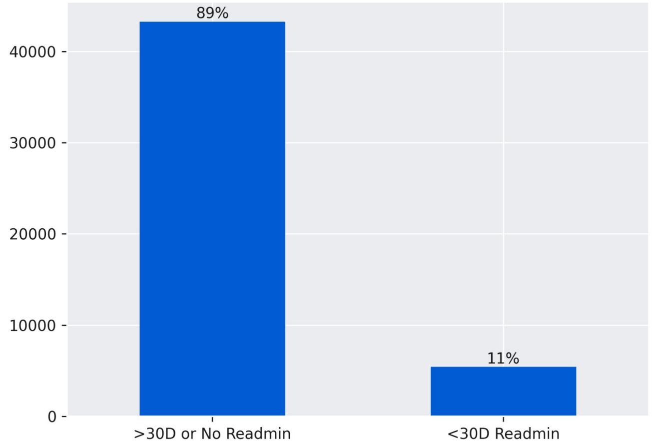
- To simplify the analysis, the target was transformed into a **binary classification**:
  - **Class 0**: Includes NO and >30 readmissions
  - **Class 1**: Includes <30 readmissions

PREPARING DATA FOR MODELING

The data was preprocessed by:

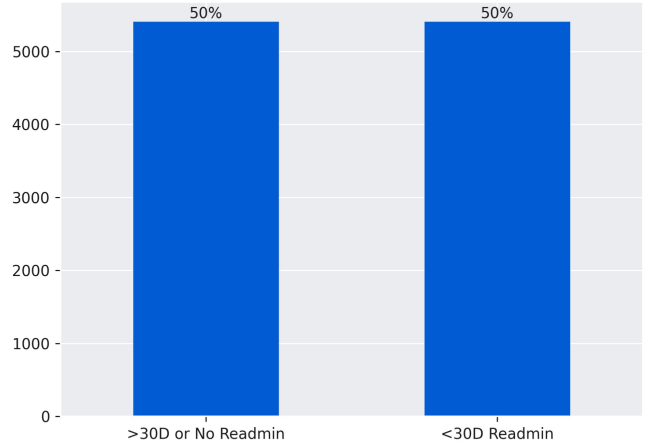
- De-noising
- Feature Engineering
- Undersampling to Address Class Imbalance

48,657 Instances



UNDERSAMPLING

10,816 Instances



METHODS AND MODELS

MODELS USED

SIMPLE

Random Forest

SVC (Support Vector Classifier)

LightGBM & **CatBoost** (Gradient Boosting)

Recurrent Neural Network (RNN)

COMPLEX

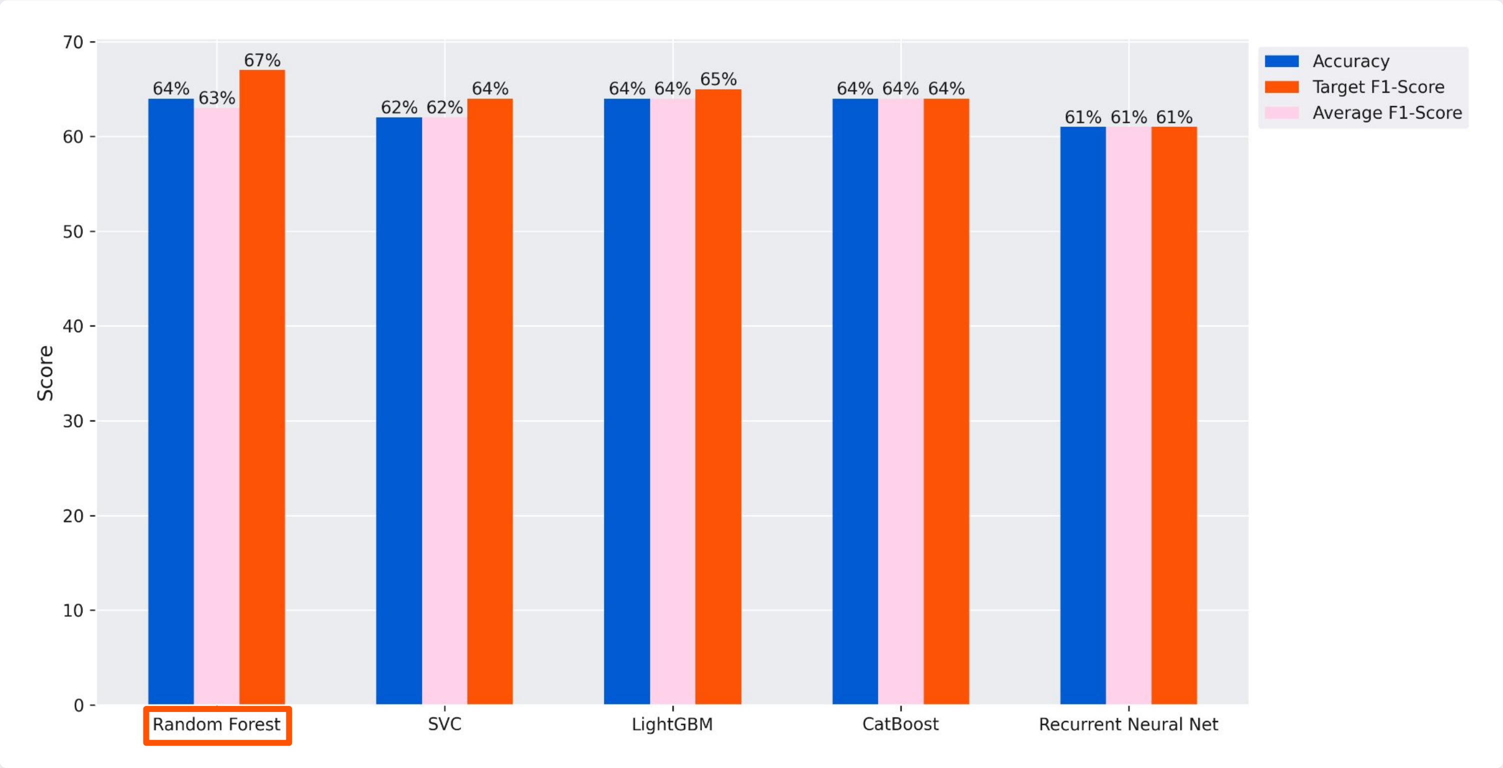
EVALUATION METHODS

- The data was split into **Train (80%)** and **Validation (20%)** sets
  - Models learn the train set
  - Models evaluated on validation set performance

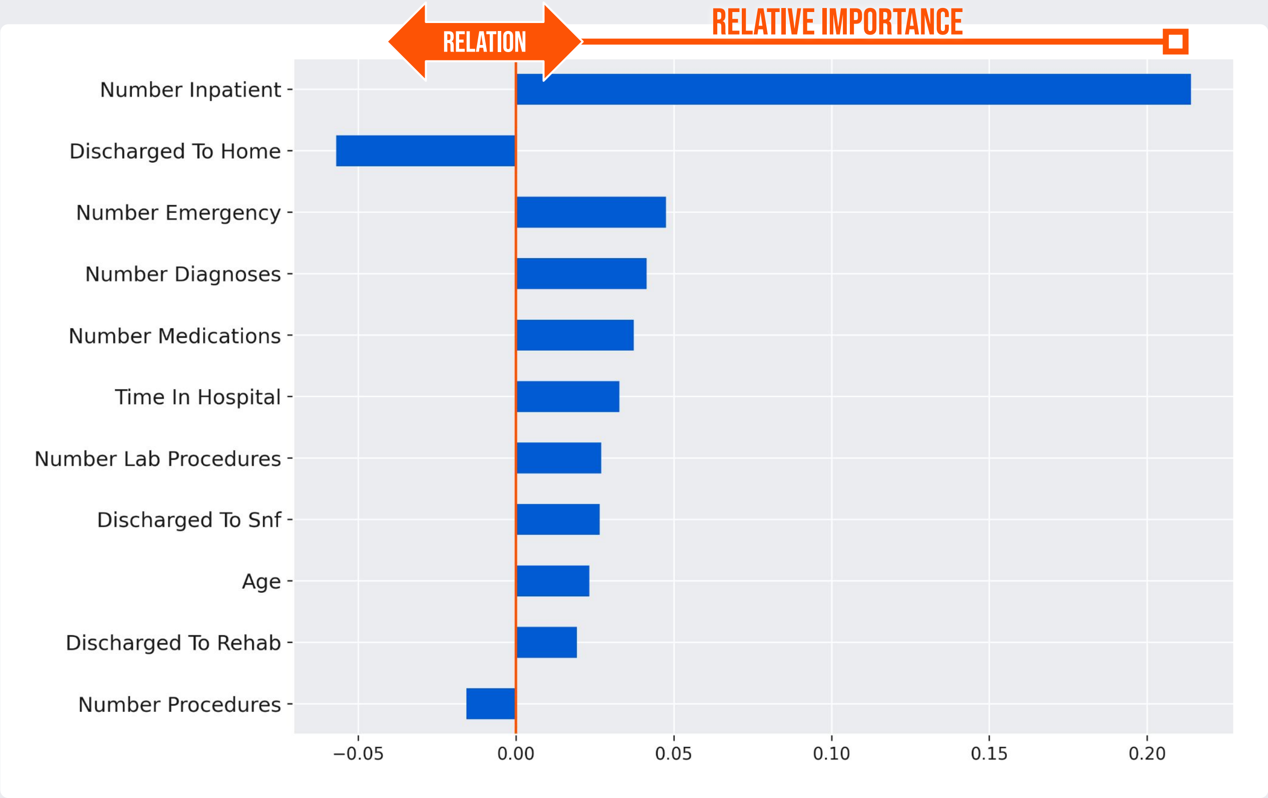
- Models were evaluated on their…
  - **Accuracy** - percent correct
  - **F-1 Score** - how accurate a machine learning model is at correctly identifying positive cases, while also minimizing errors

RESULTS

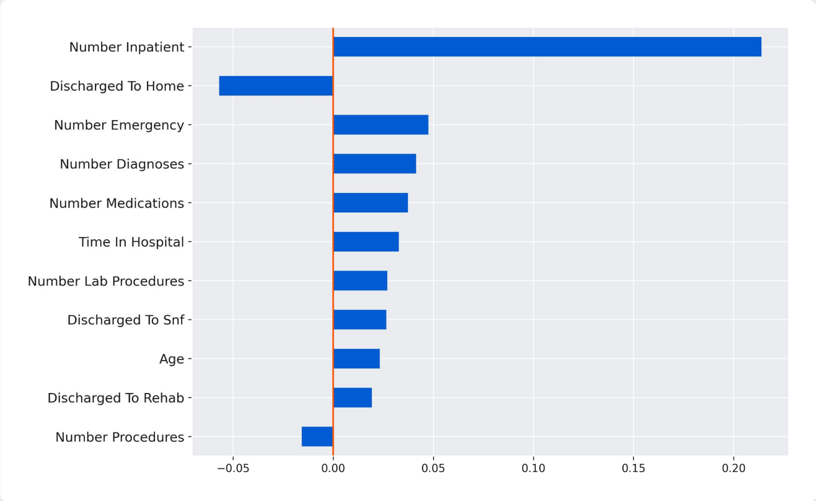
MODEL PERFORMANCE



IMPORTANT FEATURES



IMPORTANT FEATURES CONTINUED



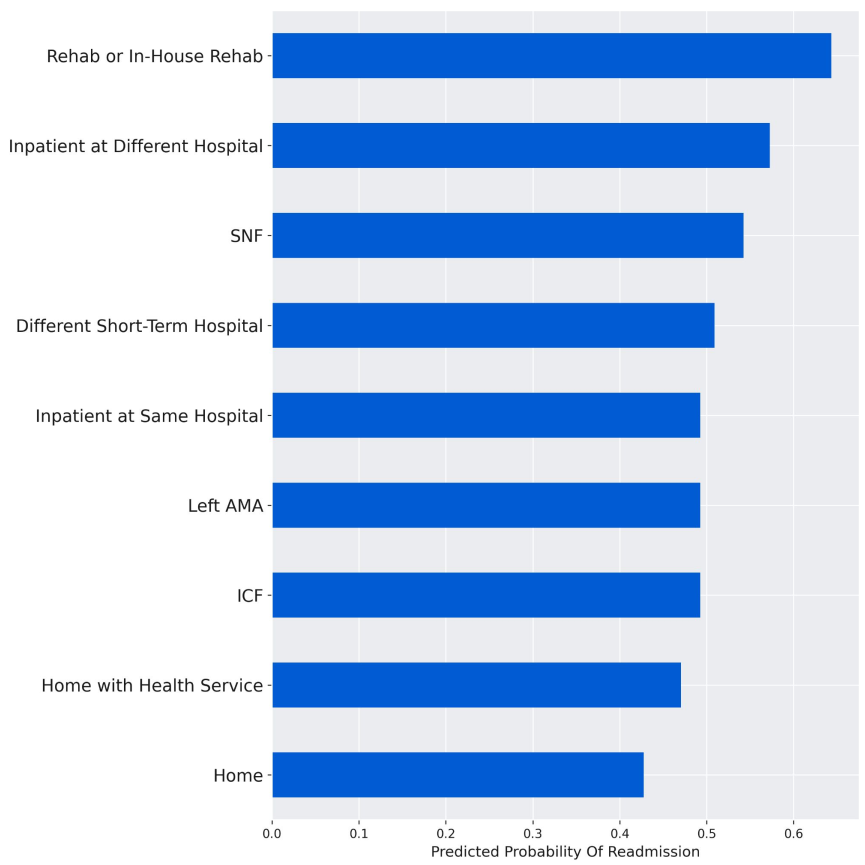
- **Correlation, not causation**

- Many of these are often **secondary to a patient's health status**, which may be the primary predictor of readmission risk
  - Hospital visits
  - Number of diagnoses
  - Number of medications
  - Discharge facility

- Interestingly, more procedures are associated with a lower risk of readmission

DISCHARGE FACILITIES BY READMISSION PROBABILITY

- **Rehab facilities** had the **highest** predicted readmission probability
- Discharge **home** had the **lowest** predicted readmission probability
- Transferring to inpatient care at the **same hospital** was associated with a **lower readmission probability** than transferring to a **different hospital**
- Again, these findings demonstrate **correlation, not causation**



VALUE AND APPLICATION

DEPLOYMENT AND APPLICATION

- The model can be integrated with **electronic health record (EHR)**
- Assess patients' risk of readmission in **real-time**
- Allow healthcare providers to intervene early and provide **targeted interventions** and **informed care plans**

BENEFITS OF A 30-DAY READMISSION PREDICTION MODEL

1. **Real-time** risk assessment
2. **Informed** care and discharge plans for high-risk patients
3. Optimized resource allocation
4. **Quality improvement (QI)** initiatives

CONCLUSION

- Hospital Readmissions…
    - Negatively impact patient outcomes
    - Decrease profits via Medicare's HRRP
    - Increase healthcare costs
    - Strain healthcare system capacity

- Our model can help providers…
    - **identify** high-risk patients
    - **improve** patient outcomes
    - **reduce** healthcare costs
    - **optimize** resource allocation

THANK YOU!

QUESTIONS?

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