NO SECOND STAY: PREDICTING 30-DAY HOSPITAL READMISSIONS

DSC450 | Team Presentation

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INTRODUCTION

Hospital readmissions within 30 days are costly and common

Goal: use data to predict patients at risk of being readmitted

Approach: machine learning on synthetic EHR dataset (30,000 patients)

BUSINESS PROBLEM / HYPOTHESIS

Can we predict 30-day readmission using clinical and demographic data?

Hypothesis: Discharge destination and chronic conditions increase risk

METHOD & ANALYSIS

1

Preprocessing: handled missing values, encoded variables, cleaned features

2

Exploratory Data Analysis (EDA) to check distributions and imbalance

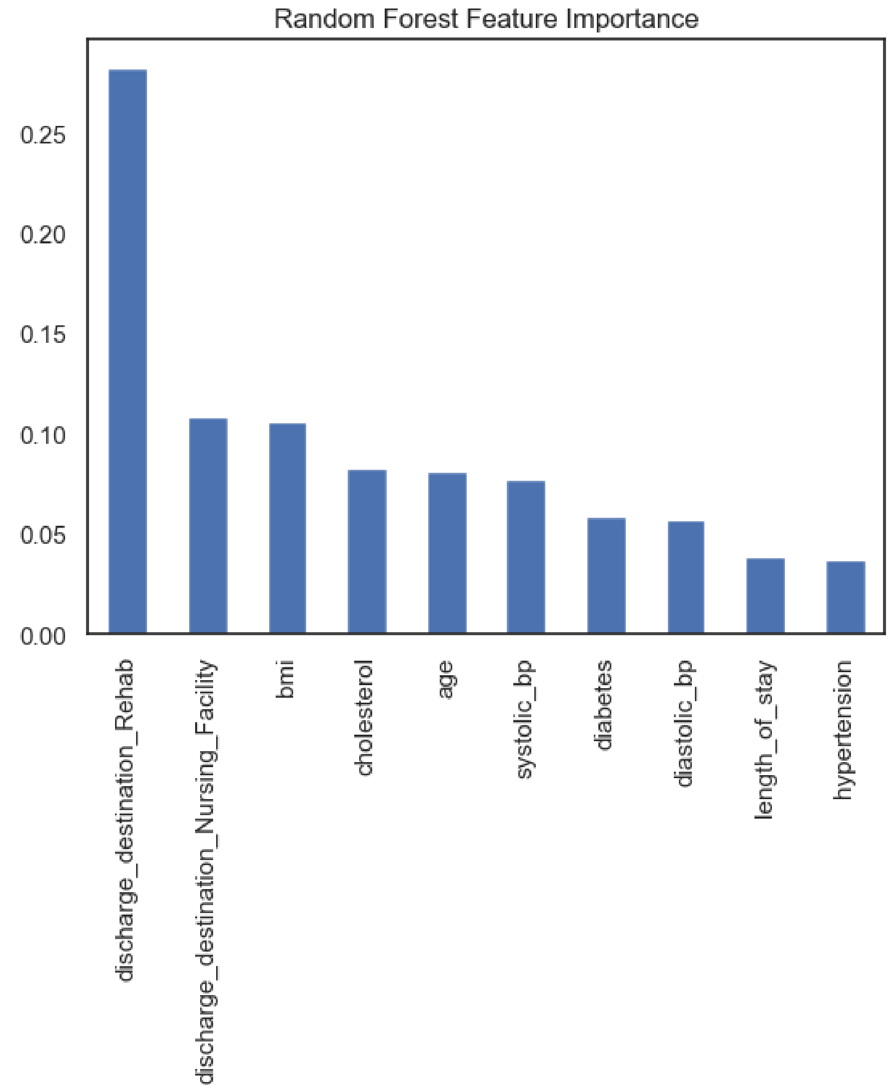
3

Modeling: Random Forest & XGBoost with GridSearchCV tuning

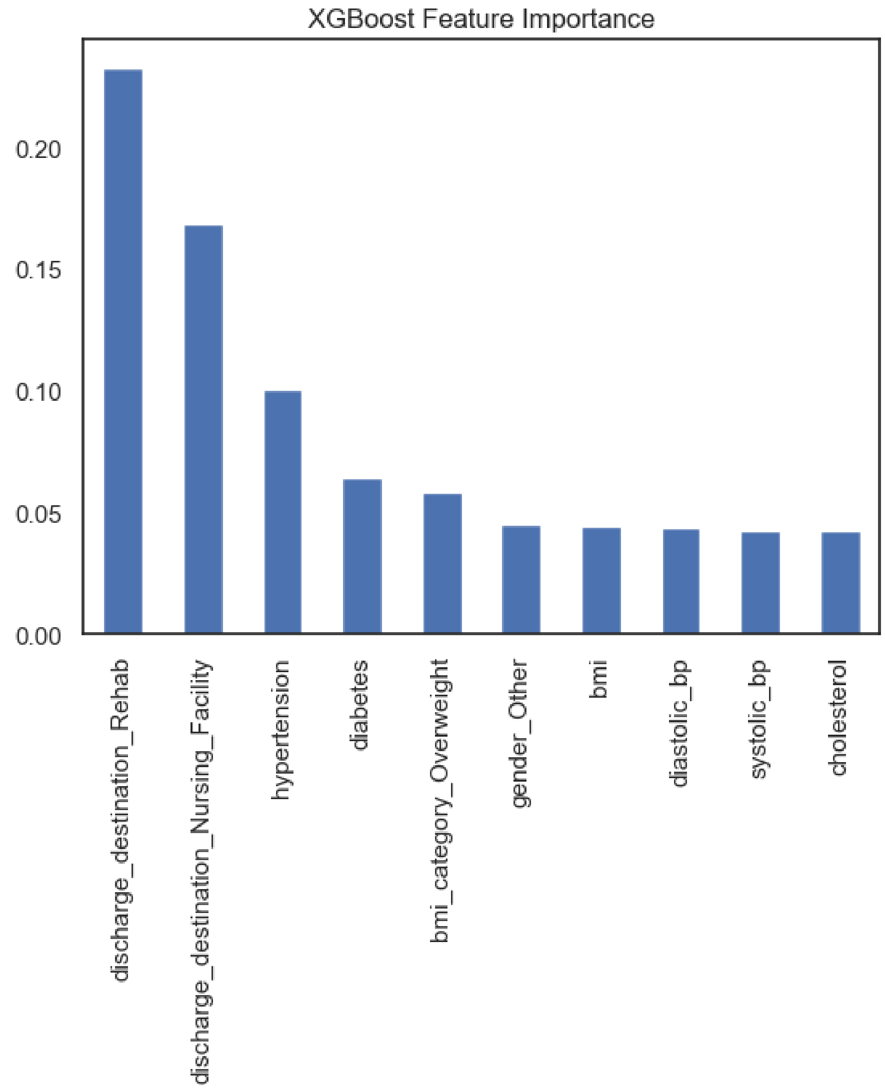
4

Evaluation: stratified 80/20 split, ROC-AUC, precision, recall, F1-score

FEATURE IMPORTANCE (RANDOM FOREST)



FEATURE IMPORTANCE (XGBOOST)

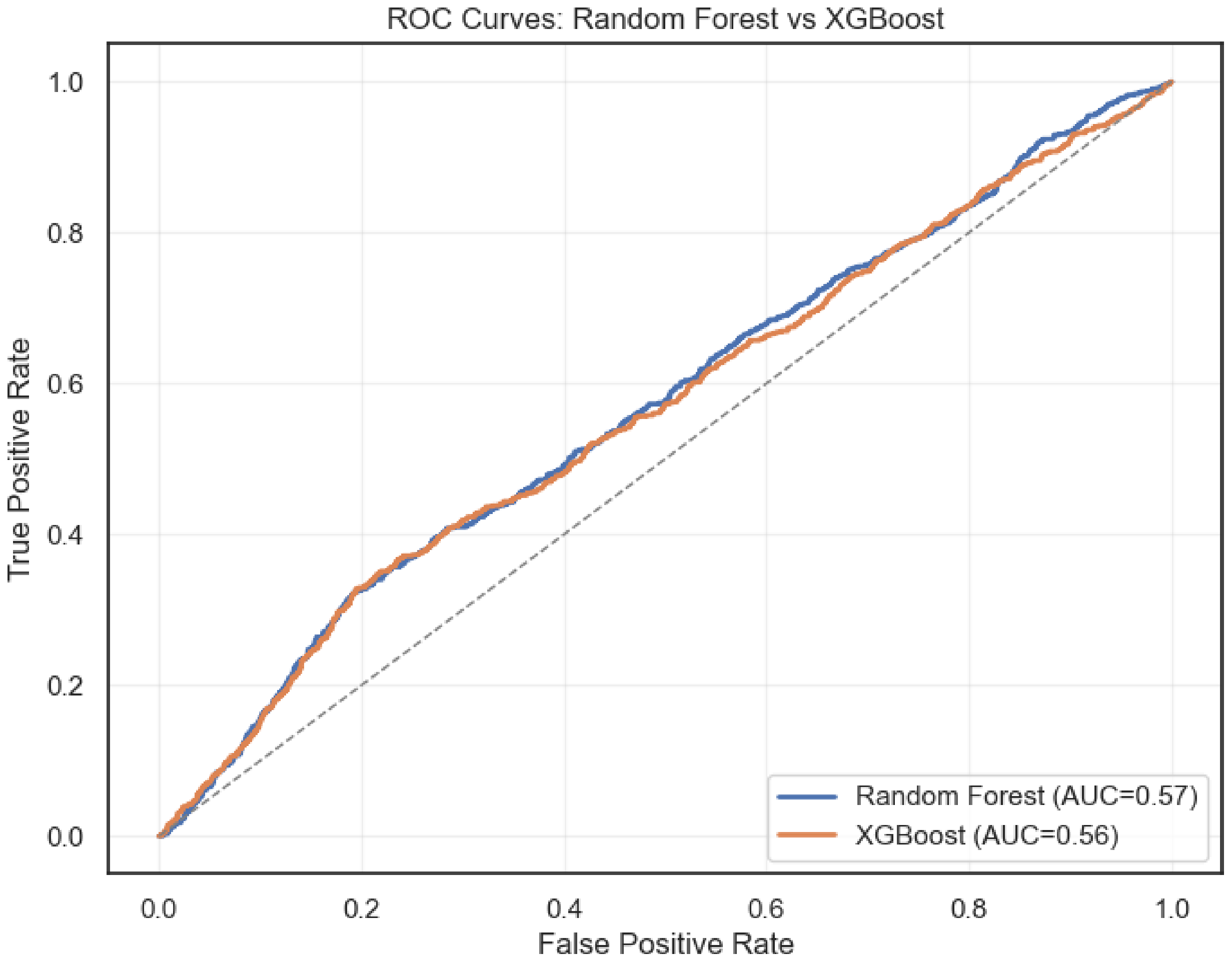


KEY FEATURE INSIGHTS

Top predictor: discharge to rehab or nursing facility

Other drivers: BMI, cholesterol, hypertension, diabetes

XGBoost also picked up gender and BMI category



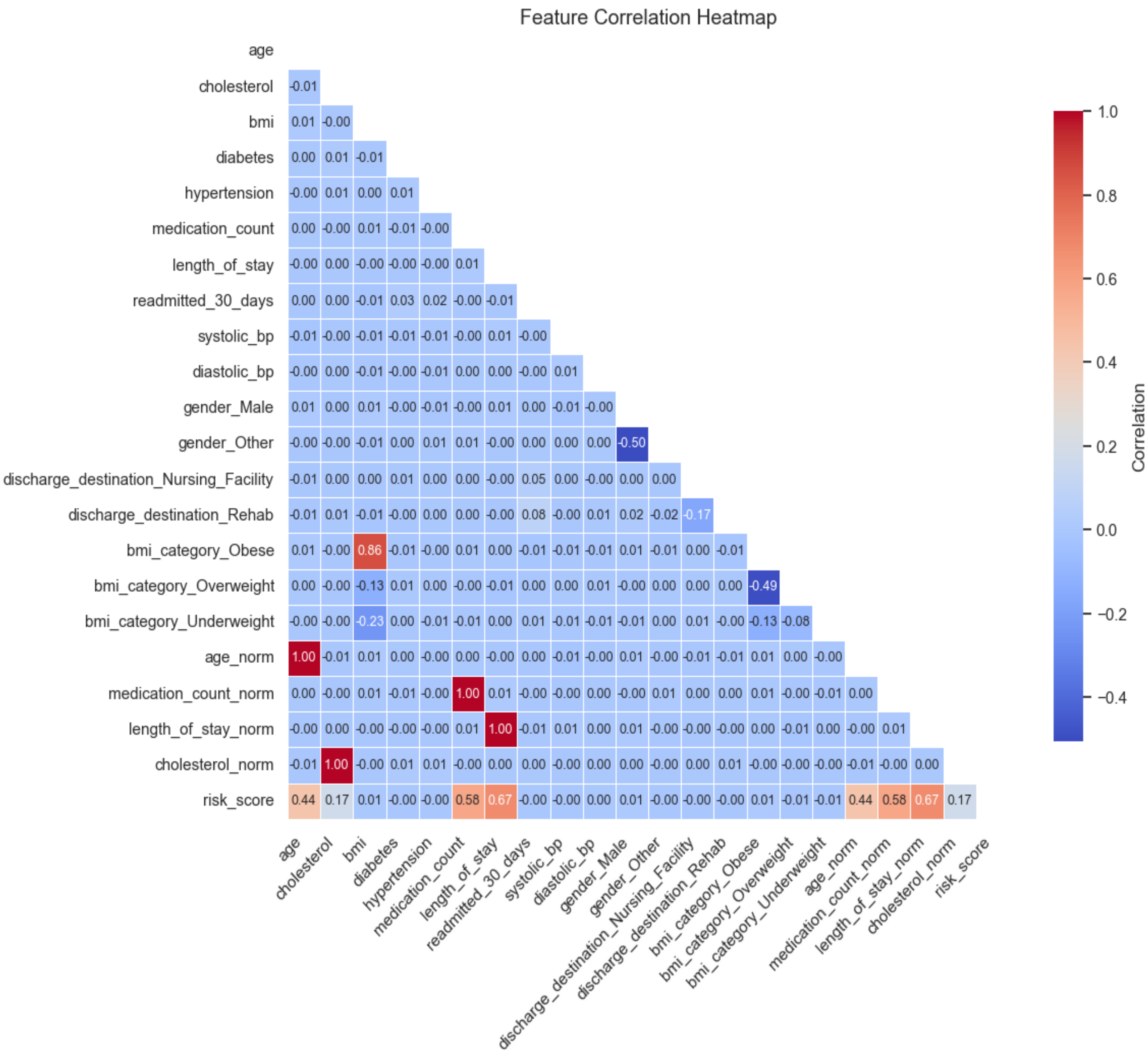
ROC CURVE: RF VS XGB

MODEL PERFORMANCE

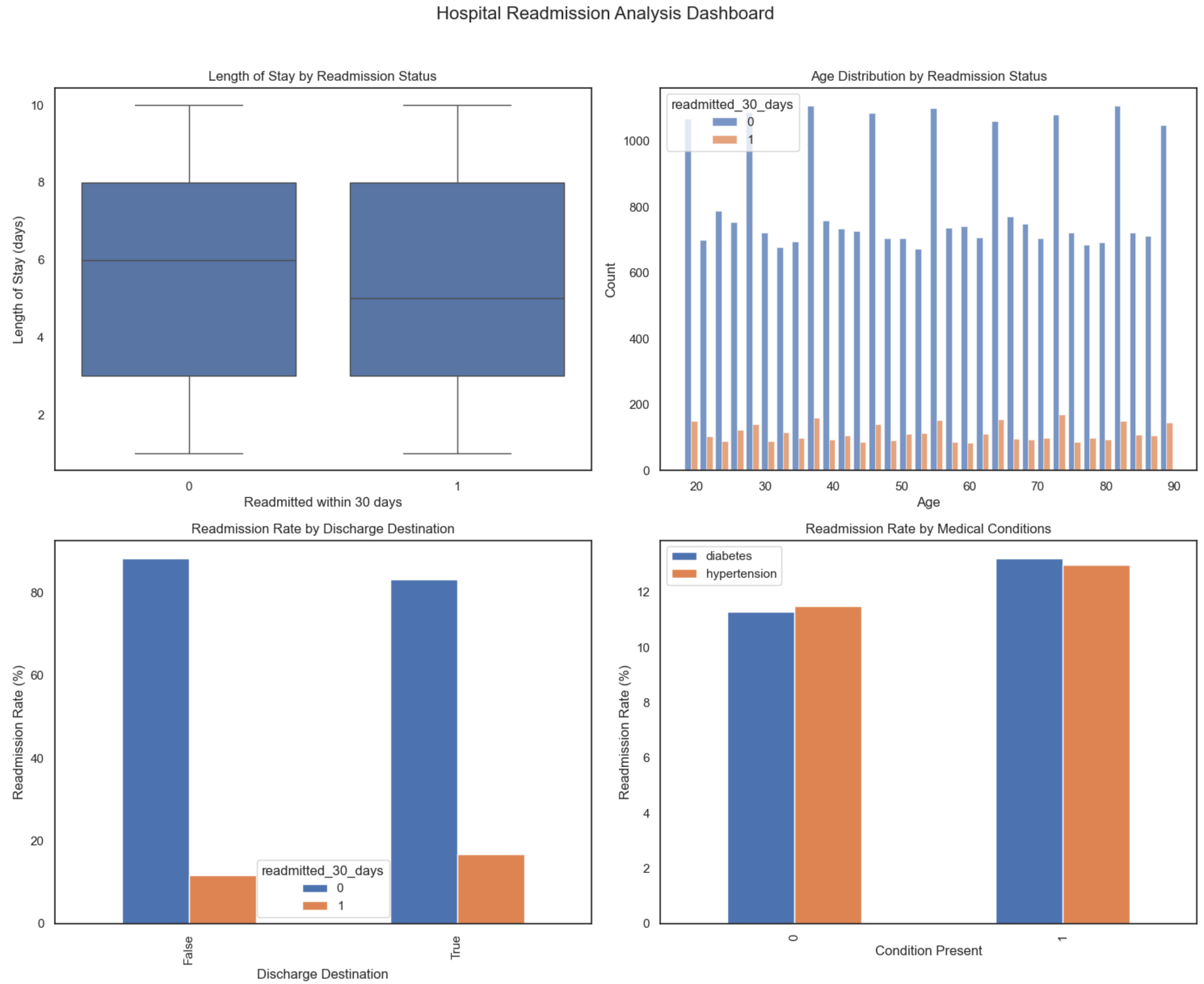
ROC curves show low improvement from random guessing

Random Forest AUC = 0.57, XGBoost AUC = 0.56

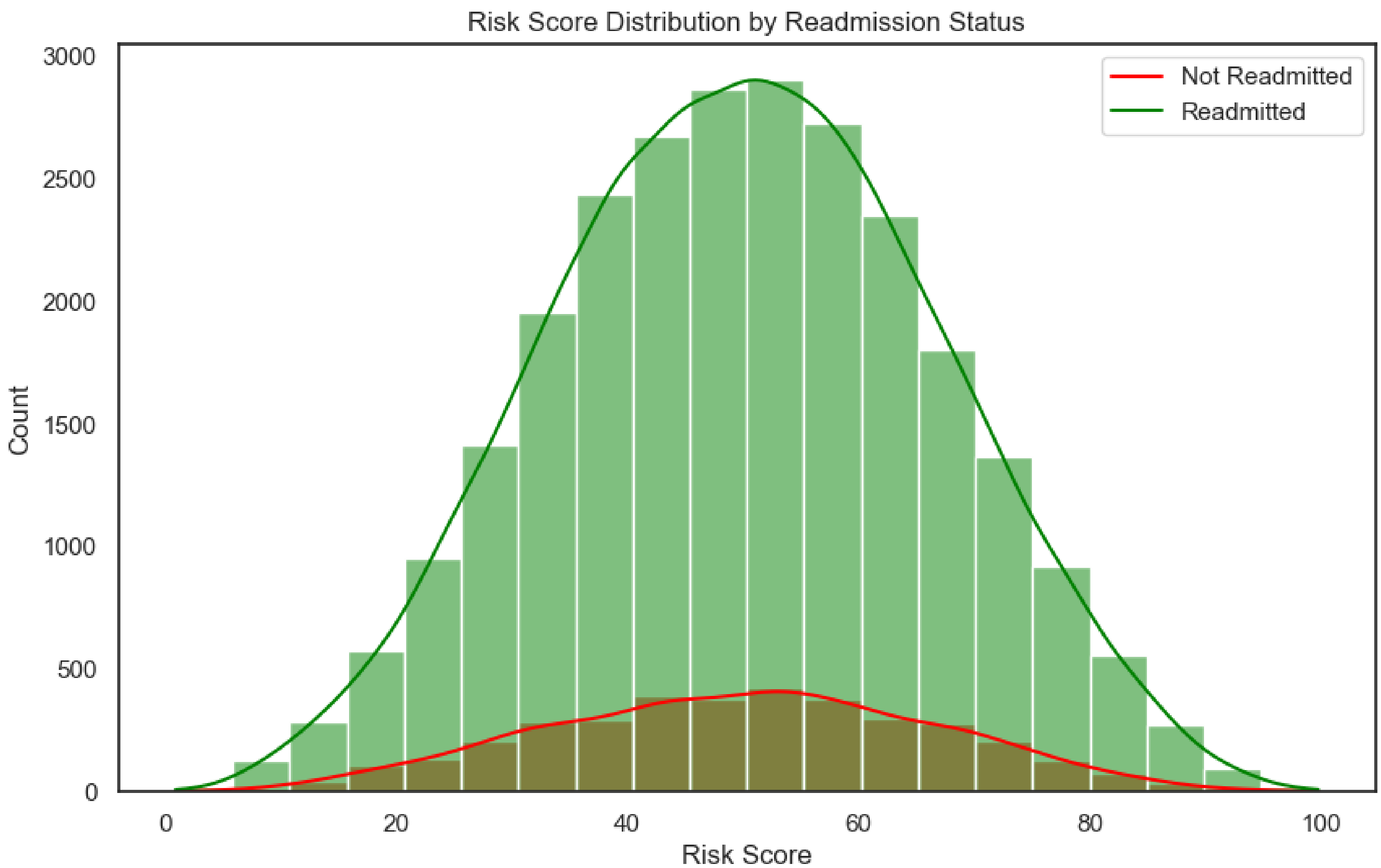
Low AUC suggests room for improvement in model design or data quality



CORRELATION BETWEEN FEATURES

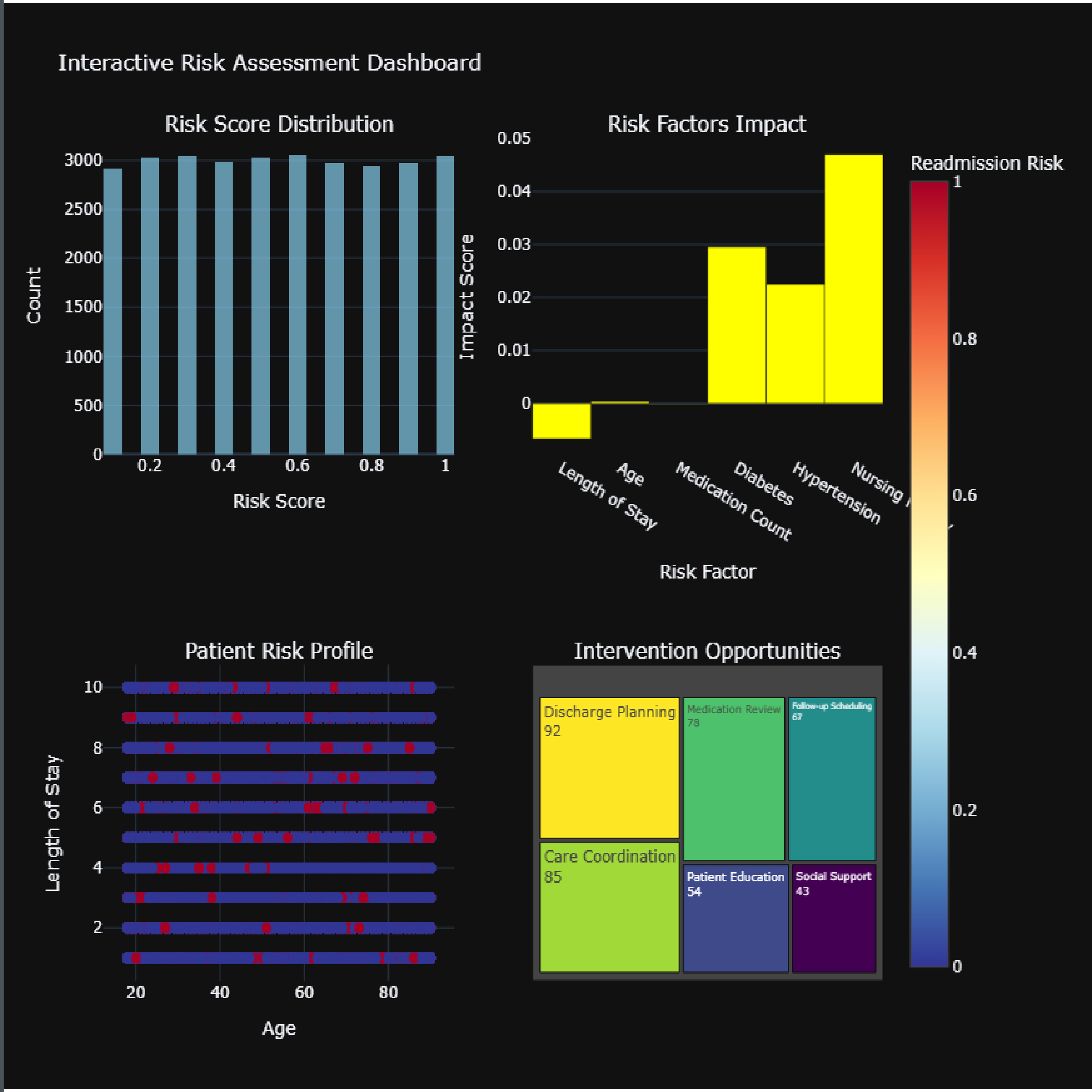


READMISSION ANALYSIS DASHBOARD



RISK SCORE DISTRIBUTION BY READMISSION STATUS

RISK & INTERVENTION OPPORTUNITIES



RECOMMENDATIONS & ETHICS

Use	Avoid	Validate
Use predictions to trigger follow-ups, not automate care decisions	Avoid bias and protect patient privacy	Validate models with real-world data before deployment

CONCLUSION

- OUR HYPOTHESIS WAS SUPPORTED: DISCHARGE DESTINATION AND CHRONIC CONDITIONS ARE KEY RISK FACTORS
- BOTH MODELS IDENTIFIED STRONG PREDICTORS LIKE REHAB DISCHARGE, HYPERTENSION, AND BMI
- MODEL PERFORMANCE WAS MODEST (AUC ~0.56–0.57), BUT SHOWED MEANINGFUL PATTERNS
- RISK SCORING AND DASHBOARDS OFFER PRACTICAL TOOLS FOR CLINICAL DECISION-MAKING
- FUTURE IMPROVEMENTS INCLUDE ADDING NEW FEATURES, VALIDATING WITH REAL DATA, AND REFINING MODEL DESIGN
- PREDICTIVE MODELING CAN HELP REDUCE UNNECESSARY READMISSIONS—AND SUPPORT BETTER OUTCOMES

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