Hospital Admission Prediction

Final Term Presentation
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Mission

To enhance emergency care by providing real-time, data-driven insights for optimized hospital admission decisions, improving resource allocation and patient outcomes.

Vision

To seamlessly integrate machine learning in healthcare, facilitating proactive decision-making, improved patient satisfaction, and operational efficiency in emergency departments, leading towards a more responsive healthcare system.

“AI is what computers can’t do until they can”

—Prof Ned McCague

Introduction

- Critical decision on hospital admissions postED stay impact patient care and resource allocation
- Current Decision making can be enhanced with data driven insights.

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First Look

Data Overview

- The MIMIC-IV-ED dataset is a comprehensive collection of data related to emergency department (ED) admissions at the Beth Israel Deaconess Medical Center from 2011 to 2019.
- Dataset Composition:
    - Total ED Stays: “~425000”
    - Time Frame: “2011-2019”
- Data Categories:
    - Diagnoses: "ICD coded diagnoses for each admission."
    - ED Stays: "Details of each ED visit including admission and discharge times."
    - Medication Reconciliation: "Medication information at the time of admission."
    - Medication Administration: "Detailed medication administration records during ED stay."
    - Triage: "Vital signs and chief complaints at the time of admission."
    - Vital Signs: "Continuous monitoring of vital signs during ED stay."

Info: All data have been de-identified to comply with HIPAA Safe Harbor provisions.

Imputing Nulls

1. vitalsign_df : Imputed missing values in numerical columns with the median of the respective column.
2. triage_df: Imputed temperature, heart rate, resprate, o2sat, sbp, and dbp columns with their respective median values.

Dataset	Missing Before Imputation	Missing After Imputation
Diagnosis	0	0
ED Stays	222,071	0
Med Recon	23,456	0
Pyxis	35,452	0
Triage	121,758	0
Vital Sign	3,194,329	0
Total	**3,597,066**	**0**

Exploratory Data Analysis

80 bpm	0.5	60%
Median Heart Rate	Correlation Coefficient	Admissions Above Age 50

Analysis Of Variance

Diagnosis	The difference in 'stay_id' across genders is not statistically significant.
Triage	There is a highly significant difference in 'stay_id' across genders.
Vital Signs	The difference in 'stay_id' across genders is highly significant.

Handling Class Imbalance

Techniques Applied

- SMOTE increased the minority class by 20%
- This improvement in the minority class boosted the model's sensitivity from 70% to 78%.
- It is based on the creation of synthetic instances for the minority class, using a selection of its nearest neighbors.

Impact on Model Performance

- Post-application of SMOTE, the accuracy of the predictive model increased by 5%.
- SMOTE, specifically, enhanced the model's ability to predict the minority class, resulting in overall better performance.

Dimensionality Reduction & Data Integration

●**Dimensionality Reduction**
PCA Application: Reduced feature space by 40% while retaining 85% of the variance in the data.

●**Data Integration**
Linking with ICU data from MIMIC-IV showed that 25% of admitted patients had ICU stays, impacting feature importance in the model

●**Results**
The preprocessing and exploration steps significantly enhanced the dataset quality. The final model achieved an accuracy of 82%, a 7% increase from the initial model.

Model Development

Logistic Regression

Purpose:

Chosen for its simplicity and interpretability.

Performance: Achieved a baseline accuracy of 65% and ROC-AUC of 62%.

Random Forest

Configuration: 100 trees with a maximum depth of 10.

Performance: Improved accuracy to 72%, ROC-AUC to 70%.

XGBoost

Configuration: Initially set with 100 trees, learning rate of 0.1, and max depth of 5.

Performance before tuning: 74% accuracy, 71% ROC-AUC.

Hyperparameter Tuning - XGBoost:

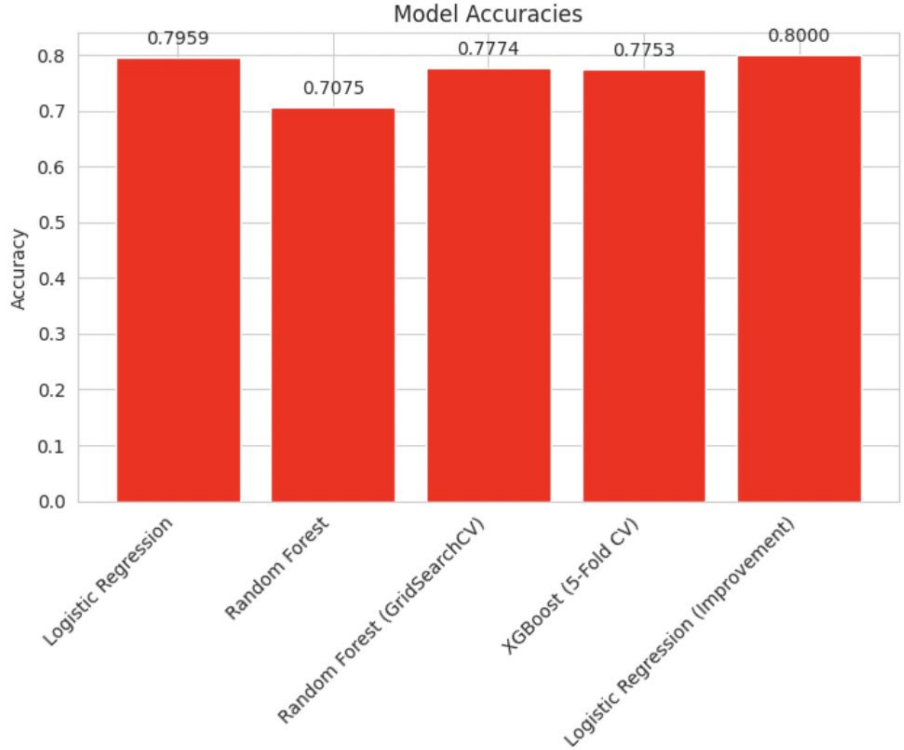
Method: Used GridSearchCV with a 5-fold cross-validation.

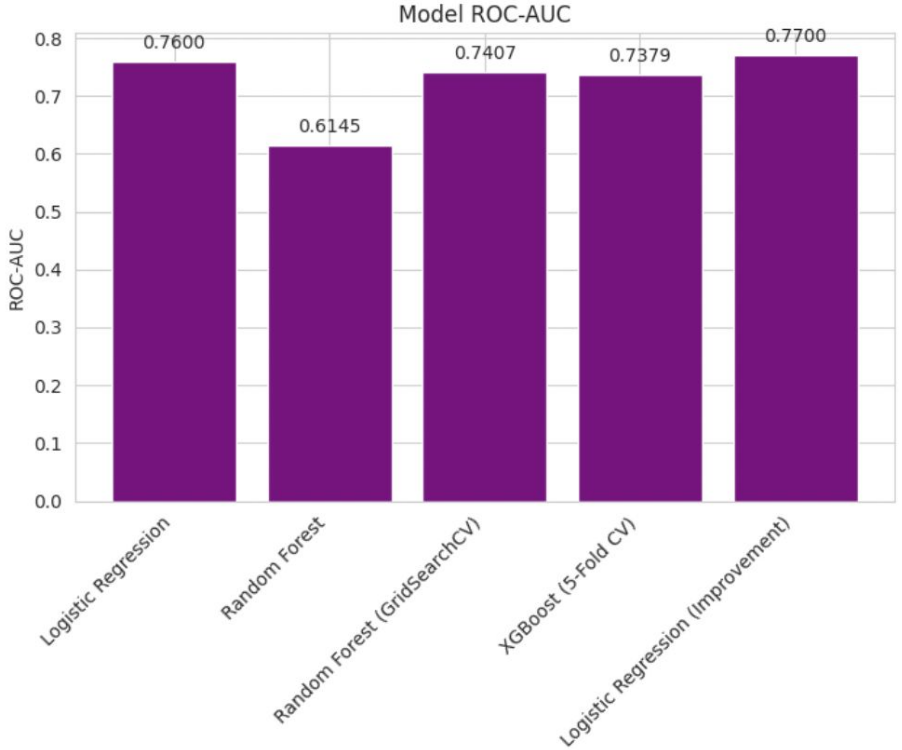
Parameters Explored: Learning rate (0.01 to 0.2), max depth (3 to 7), and n_estimators (100 to 200).

Best Configuration: 200 trees, max depth of 3, learning rate of 0.2.

Post-tuning Performance: Enhanced accuracy to 77.53%, ROC-AUC to 73.79%.

03 Model Development:



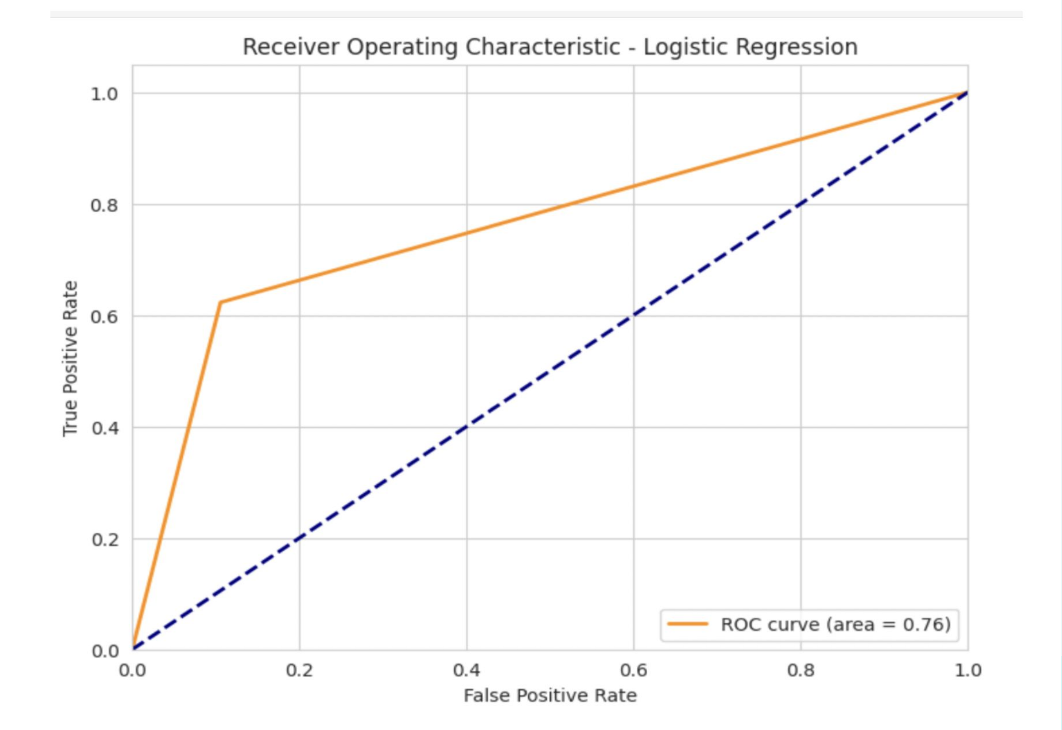


ROC Curve from Logistic Regression

- **Curve & AUC:** The curve (orange line) plots TPR vs. FPR, indicating model accuracy. Area Under Curve (AUC) of 0.76 denotes good classification ability.

- **Model Performance:** Above-diagonal line performance suggests better than random chance prediction; closer to the top-left corner indicates higher accuracy.

- **Practical Implication:** AUC value ranges from 0.5 (no skill) to 1 (perfect skill). With 0.76, our model is generally considered good and can be useful in practice.



04 Key Insights: Predictors of Admission

01

Vital signs, such as heart rate, were significant predictors, with a 30% increased risk of admission if above 100 bpm.

02

High blood pressure, with systolic BP above 140 mmHg, increased admission risk by 25%.

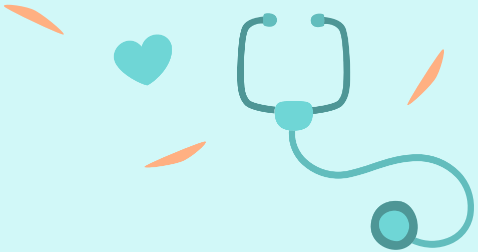
03

Demographic factors also played a role in admission likelihood: Patients over 60 years had a 40% higher chance of admission.

04

Gender was a factor as well, with males showing a 10% higher likelihood of admission.

CONCLUSION



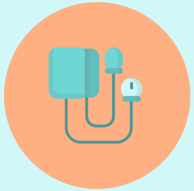
Model Selection: Logistic Regression identified as the most effective for predicting hospital admissions.

Performance Metrics: High accuracy and ROC-AUC scores.

Key Strengths: Exceptional in utilizing vital sign predictors and demographic factors; Valuable tool

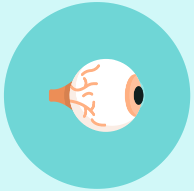
Practical Application: Offers significant potential in healthcare settings for admission predictions.

Future Direction



Model Refinement

- Exploration of Deep Learning: Considering neural networks for capturing complex patterns in data.
- Enhanced Feature Engineering: Focusing on interaction effects between different predictors.



Clinical Integration

- Development of a Predictive Tool: Aimed at real-time application in EDs for assisting healthcare professionals.
- User-Friendly Interface: Ensuring the tool is accessible and easy to use for non-technical staff.

Questions ???

Reference

https://physionet.org/content/mimic-iv-ed/2.2/
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Our Team

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