Predicting Hospital Readmission Following Acute Kidney Injury

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Clinical Problem of Acute Kidney Injury Readmissions

Acute Kidney Injury (AKI): Incidence of sudden kidney damage, limiting the body's capability to filter blood and urine for nutrients and waste

Negatively Impacts Patient Prognosis and Increases Strain on Hospital Resources

Leads To: Cardiovascular Disease, Chronic Kidney Disease, Infections, More

AKI Hospital Discharge: Causes increased risk of readmission or death within 90 days

Hospitals Need a Generalizable and Accurate Scoring System for Predicting Post-AKI Hospital Readmission

Aims

1. **Characterize Readmission Post Hospitalization and Identify Risk Factors**
2. **Develop a Post-AKI Readmission Prediction Model**
3. **Establish a Patient-Level Readmission Score**

Significance and Innovation

Significance? Contributes a scoring system for personalized, data-driven interventions to target follow-up care and reduce readmission rates for high risk patients

Innovation? Utilizing comprehensive KPMOCE electronic health record (EHR) data integrated with the Hopkins PMAP platform to advance beyond limited single-center cohorts

Applied Clinical Value? Guides readmission prevention strategies allowing for optimization of hospital resource allocation and enablement of targeted interventions

References

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Scholarly citations · Methodological frameworks · Clinical relevance

https://bit.ly/teamFalconref

Results

1A CHARACTERIZATION OF READMISSION POST HOSPITALIZATION:

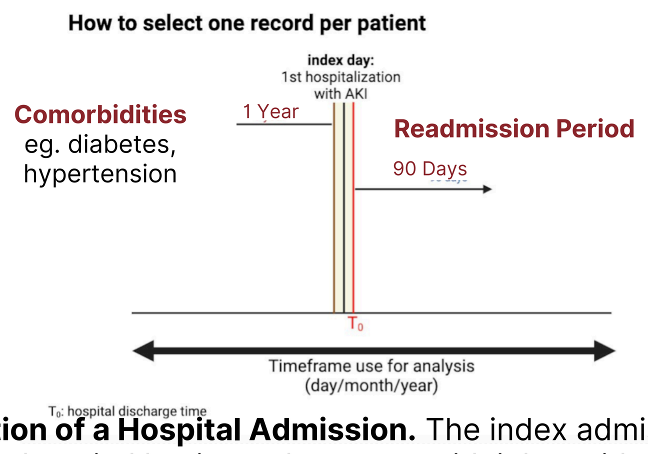

Figure 1. Definition of a Hospital Admission. The index admission is defined as the first stay at a hospital lasting at least two midnights with readmission period being 90 days following discharge.

1B IDENTIFICATION OF DATA VARIABLES AS POTENTIAL RISK FACTORS:

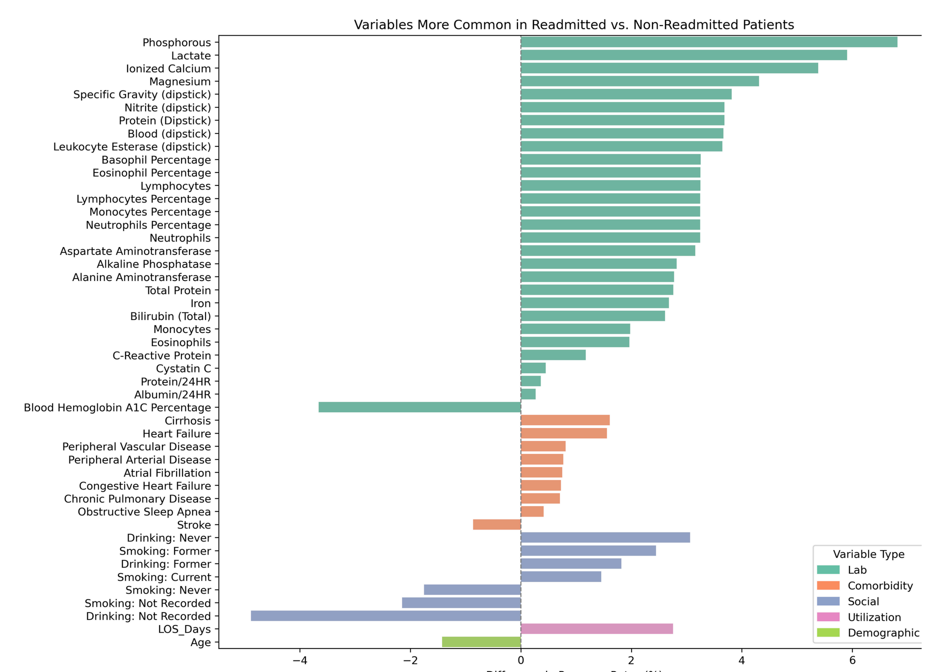

Figure 2. Differences in Clinical and Social Variables Between Readmission Groups. Significant variables (FDR < 0.05, difference ≥ 0.5%) are shown. Positive values indicate higher presence or averages in readmitted patients. Variables are grouped by type and sorted by effect size.

2 DEVELOP A POST-AKI READMISSION PREDICTION MODEL

Separate Temporal and Static Variables → Inclusion and Exclusion Criteria to Create Cohort → Train Predictive Model → Evaluate Feature Importance

Type	Features
Static	Comorbidities Demographics
Temporal	Lab and Physiological Measurements

Table 1. Categorization of Variables. Comprehensive EHR data obtained from the JHU PMAP Architecture was categorized and filed into binary or continuous data types.

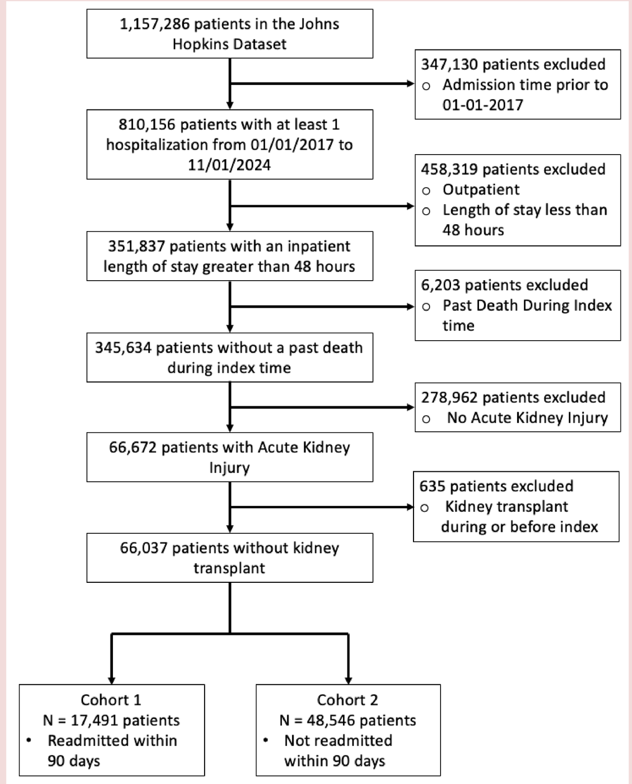

Figure 3. Inclusion-Exclusion Criteria. Patients were excluded from the cohort if outside time frame, outpatient, lacking admission, they have not had AKI, or had a kidney transplant.

Model	Training AUROC	Testing AUROC
XGBoost	0.70	0.65
CatBoost	0.72	0.65
LightGBM	0.71	0.65
Decision Tree	0.66	0.56
Random Forest	0.63	0.64
Logistic Regression	0.69	0.64
Ensemble XGBoost CatBoost LightGBM Decision Tree	0.71	0.65

Table 2. Predictive Models of Hospital Readmission. Various predictive models were tested on the cohort and their receiver operating characteristic (ROC) curves were plotted for comparison.

Ensemble model is a stacked model using a Histogram Gradient Boosting meta-model. XGBoost, CatBoost, LightGBM, and Decision Tree base learners were used.

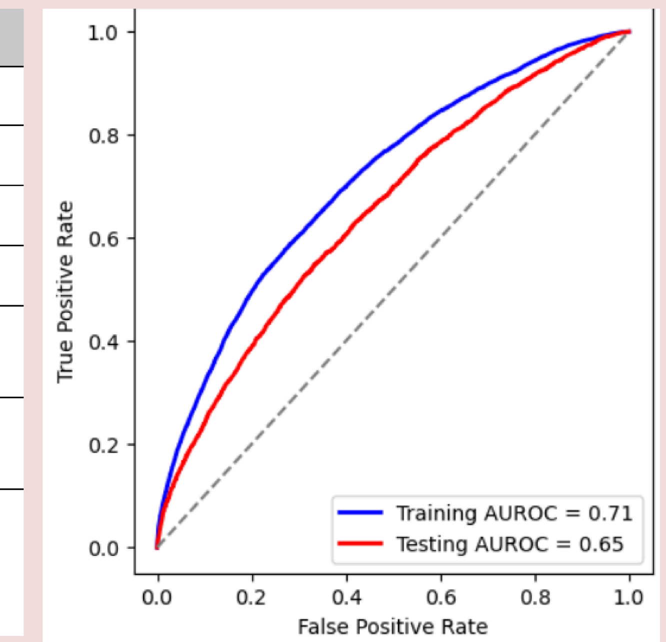

Figure 4. Ensemble receiver operating characteristic curve displaying model performance in predicting readmission. Chosen operating point for this model optimized specificity and negative predictive value. This was intended to reduce the number of false negatives, as hospital readmissions are costly within healthcare, and most importantly to the patient.

Specificity: 0.33
Sensitivity: 0.83
Positive Predictive Value: 0.30
Negative Predictive Value: 0.85

3 FUTURE DIRECTIONS: ESTABLISH A PATIENT-LEVEL READMISSION SCORE

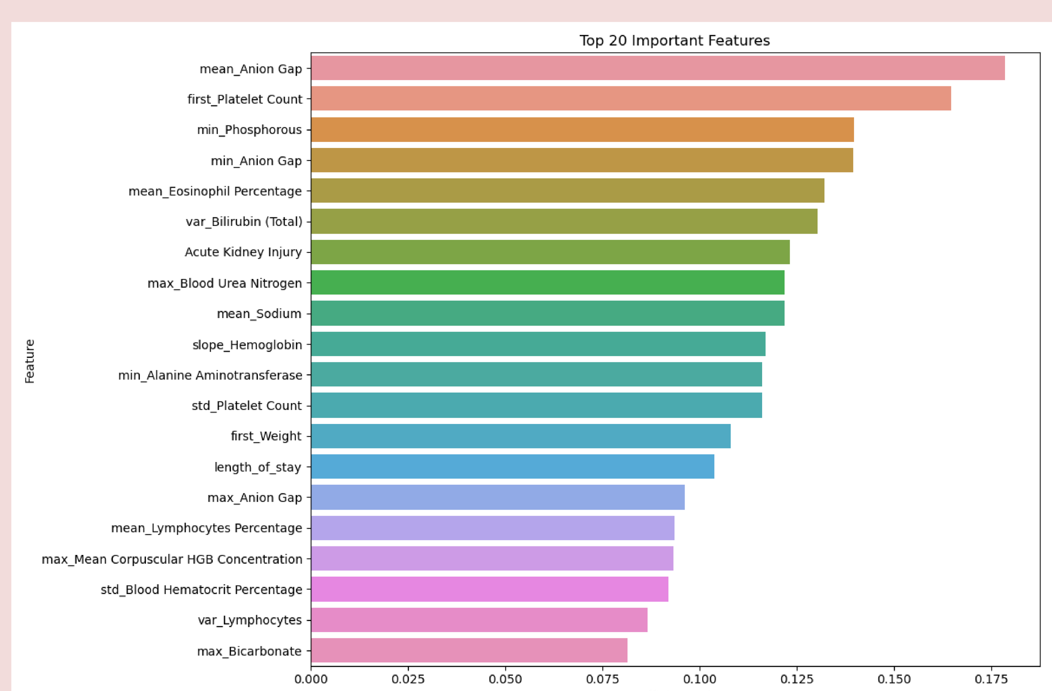

Figure 6. Feature Importance of Histogram GBM Model. Top 20 most important weighted features of the histogram GBM model utilized by the ensemble model.

Features used	AUROC	Most Impactful Ablated Features
Comorbidities ablated	0.639	Diabetes, Congestive Heart Failure, COPD, Sepsis (at Admission), Maximum AKI Stage
Demographics ablated	0.651	Age, African American Ethnicity
Lab Measurements ablated	0.607	Anion Gap, Bilirubin, Phosphorus, Sodium, Lymphocyte, Blood Urea Nitrogen, Serum Creatinine
Vital signs and Physical Exams ablated	0.579	Blood Pressure, Weight Change, Heart Rate, Respiratory Rate
All features	0.654	

Table 2. Ablation Studies. Model prediction performance and most impactful ablated features for each ablation study noted above.

Conclusion

1. Rich, Multi-Center Cohort: We built a large post-AKI inpatient cohort (> 60 k admissions), capturing both static (demographics, comorbidities) and temporal (labs, vitals, physiologic trends) data streams.

2. Robust Predictive Performance: A stacked gradient-boosting ensemble (XGBoost + CatBoost + LightGBM) predicts 90-day, all-cause readmission with a validated AUROC ≈ 0.65, outperforming conventional logistic regression and single-tree models.

3. Actionable Clinical Insights: Feature importance and systematic ablation highlight dynamic vital signs and bedside physiological measures as the strongest drivers of risk—laying the groundwork for a concise, bedside-ready post-AKI readmission score.

Acknowledgements

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