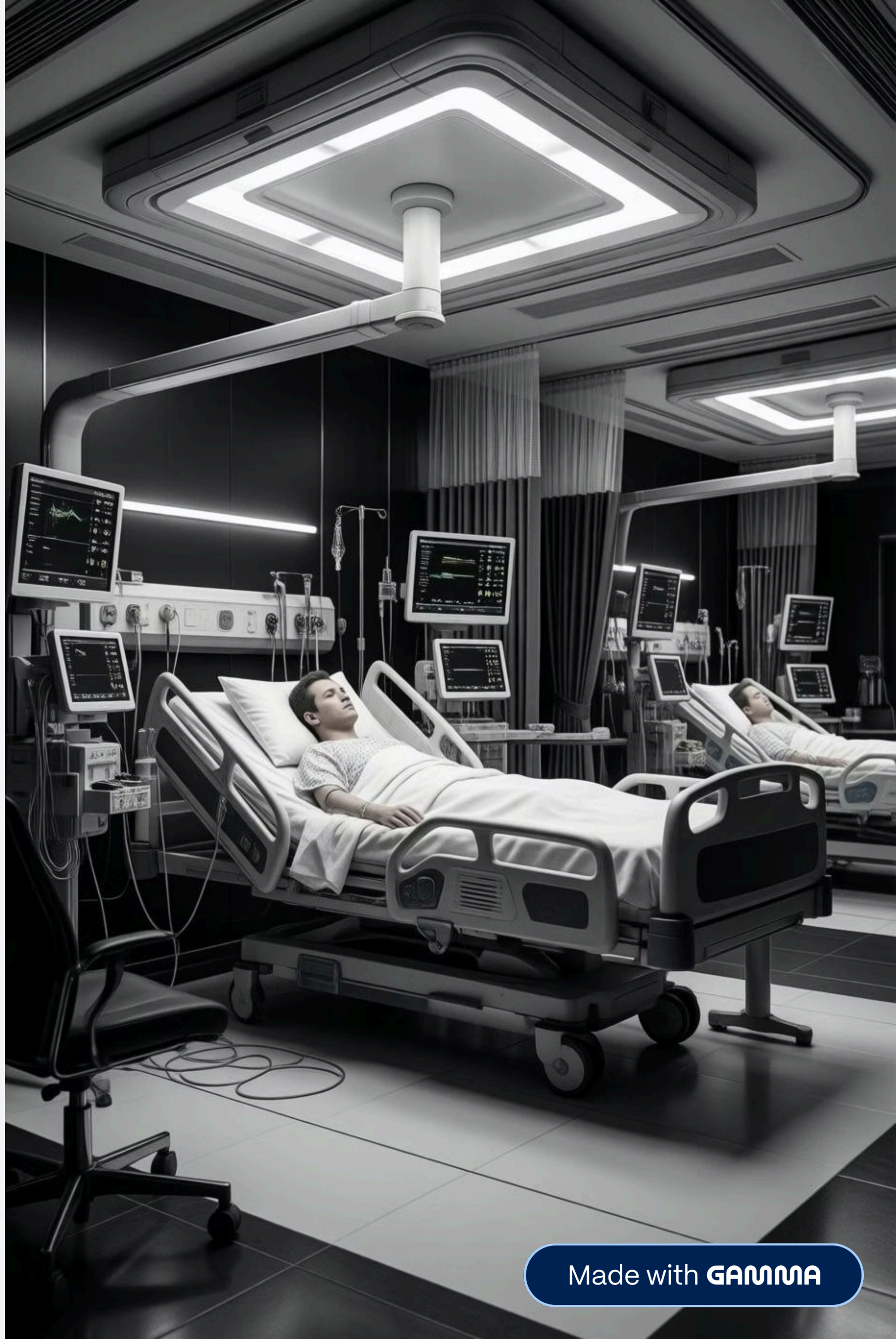
Machine Learning-Based Prediction of ICU Mortality

A retrospective cohort study using MIMIC-III electronic health record data to develop and validate predictive models for in-hospital mortality in adult intensive care patients

CRITICAL CARE RESEARCH

PREDICTIVE ANALYTICS



INTRODUCTION

The Critical Need for Mortality Prediction

Clinical Challenge

Early identification of high-risk ICU patients remains essential for optimal resource allocation, timely interventions, and informed decision-making. Traditional severity scoring systems like APACHE and SOFA have limitations in capturing patient complexity and require manual calculations.

Machine Learning Advantage

- Identifies complex non-linear relationships between predictors
- Provides automatic feature importance ranking
- Enables real-time, scalable predictions
- Continuously improves with new data

Study Objective: Develop and validate machine learning models for predicting in-hospital mortality using routinely collected EHR data from 25,324 ICU admissions.

METHODS

Data Source and Study Design

Database

MIMIC-III v1.4: 53,423 hospital admissions from Beth Israel Deaconess Medical Center (2001-2012)

Final Cohort

25,324 adult ICU admissions meeting inclusion criteria: age 18-85, ICU stay ≥24 hours, complete data

Outcome

In-hospital mortality: 2,497 deaths (9.86%) vs 22,827 survivors (90.14%)

Data integration involved joining 7 MIMIC-III tables including patient demographics, ICU stays, diagnoses, procedures, and outcomes. Rigorous data leakage prevention excluded post-admission variables.

Feature Engineering Strategy

12 Predictor Variables

- **Demographics**

  Age, gender, ethnicity (5 groups)

- **Comorbidities**

  Diabetes, hypertension, CKD, CHF, COPD, cancer

- **Clinical Features**

  Diagnosis group (12 categories), respiratory procedures, comorbidity count

Comorbidity Detection

Binary flags created using ICD-9 diagnosis code pattern matching on standardized clinical terminology:

Condition	Matching Keywords
Diabetes	"diabetes"
Hypertension	"hypertension", "high blood pressure"
CKD	"chronic kidney", "renal failure"
CHF	"heart failure", "congestive"
COPD	"copd", "emphysema", "chronic bronchitis"
Cancer	"malignan", "cancer", "carcinoma", "neoplasm"

MACHINE LEARNING APPROACH

Three Complementary Algorithms

Random Forest

500 trees, max depth 10

- Ensemble method robust to overfitting
- Handles non-linear relationships
- Balanced class weights
- Provides feature importance

XGBoost

200 estimators, learning rate 0.1

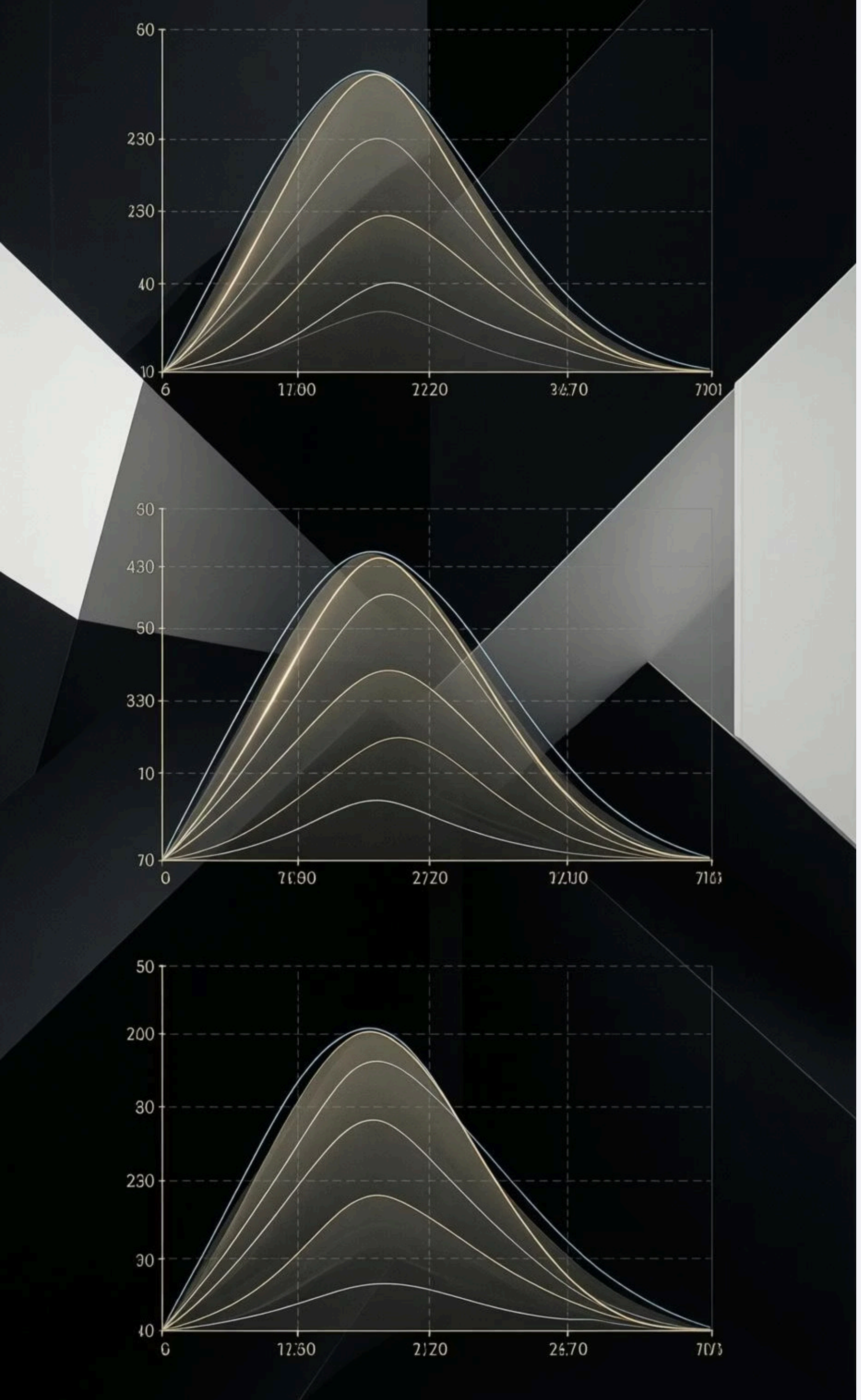
- State-of-the-art gradient boosting
- Scale_pos_weight: 9.14 for imbalance
- Early stopping to prevent overfitting
- Excellent predictive performance

Logistic Regression

Standardized features, balanced weights

- Interpretable linear coefficients
- Z-score normalized features
- Baseline comparison model
- Maximum transparency

Training Strategy: 80/20 train-test split with stratified sampling to preserve mortality rate distribution. Class imbalance addressed through inverse frequency weighting.



RESULTS

Excellent Discriminatory Performance

0.84

Random Forest AUC

Best overall balance: 77.5% accuracy, 75.2% sensitivity

0.84

XGBoost AUC

Highest sensitivity: 81.0% correctly identified deaths

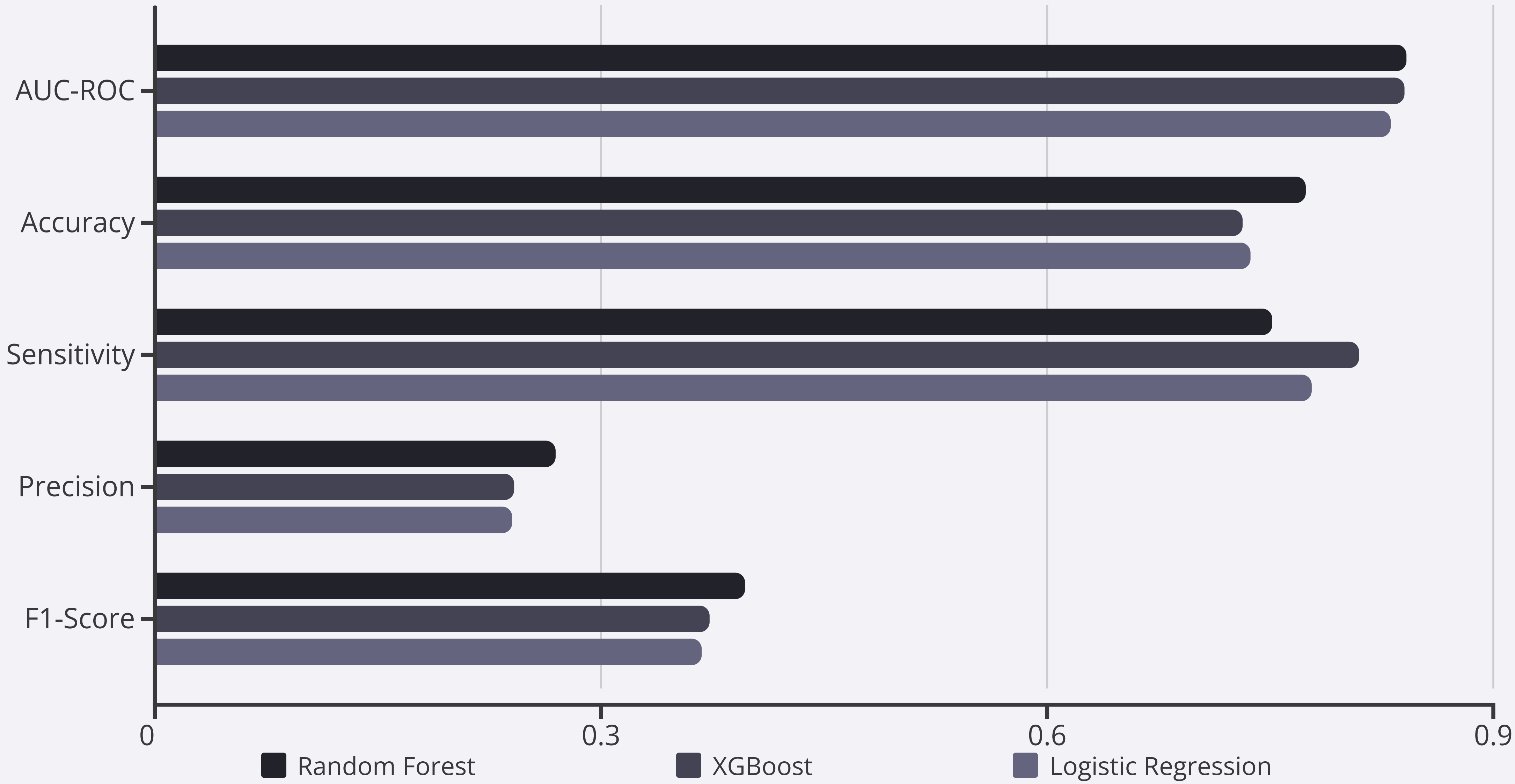
0.83

Logistic Regression AUC

Competitive performance with maximum interpretability

Clinical Interpretation: An AUC of 0.84 means these models correctly rank a randomly selected deceased patient as higher risk than a randomly selected survivor 84% of the time—substantially better than traditional scoring systems.

Model Performance Metrics Comparison



Random Forest: Best Balance

Correctly identified 375 of 499 deaths (75.2%) while maintaining 77.7% specificity. Optimal for balanced decision-making.

XGBoost: Maximum Sensitivity

Missed only 95 deaths (19.0% false negative rate)—ideal for screening high-risk patients when missing deaths is costly.

FEATURE IMPORTANCE

Respiratory Failure Dominates Mortality Risk

Respiratory Procedures

40-98% importance across models

Mechanical ventilation, intubation, and tracheostomy emerged as the overwhelming predictor of mortality, reflecting severe respiratory failure and multi-organ dysfunction.

Chronic Kidney Disease

11-50% importance

CKD complicates ICU recovery through fluid overload, electrolyte imbalances, and uremic complications.

Patient Age

1-45% importance

Non-linear relationship with mortality reflecting decreased physiological reserve in older adults.

Active Malignancy

2-20% importance

Cancer diagnosis associated with advanced disease, immunosuppression, and treatment complications.

Comorbidity Burden

1-10% importance

Cumulative effect of multiple chronic conditions capturing overall patient frailty.

CLINICAL IMPLICATIONS

Translating Predictions into Practice

Risk Stratification at Admission

Identify high-risk patients immediately upon ICU admission to enable early mobilization of critical care resources and support triage decisions during resource scarcity.

Clinical Decision Support

Real-time mortality predictions guide treatment intensity, facilitate informed family discussions regarding prognosis, and support advance care planning conversations.

Quality Improvement

Benchmark ICU performance using risk-adjusted mortality, identify patients for protocol-driven interventions, and monitor temporal trends in outcomes.

Respiratory Management Focus

Emphasize respiratory failure prevention, implement early intervention for at-risk patients, and consider non-invasive ventilation strategies to avoid intubation.

Multidisciplinary Coordination

CKD patients require nephrology involvement, age-adjusted protocols for geriatric patients, and palliative care consultation for cancer patients.

CONCLUSIONS

Machine Learning Enhances ICU Mortality Prediction

Excellent Performance

All three models achieved AUC >0.83, demonstrating superior discriminatory ability compared to traditional scoring systems while requiring fewer physiological measurements.

Random Forest Optimal

Best balance with 77.5% accuracy and 75.2% sensitivity, correctly identifying 3 out of 4 deaths at ICU admission using routine EHR data.

Respiratory Focus

Need for invasive respiratory support emerged as the dominant predictor (40-98% importance), highlighting critical pathway to mortality.

Next Steps

01

External validation on independent datasets (eICU, MIMIC-IV)

02

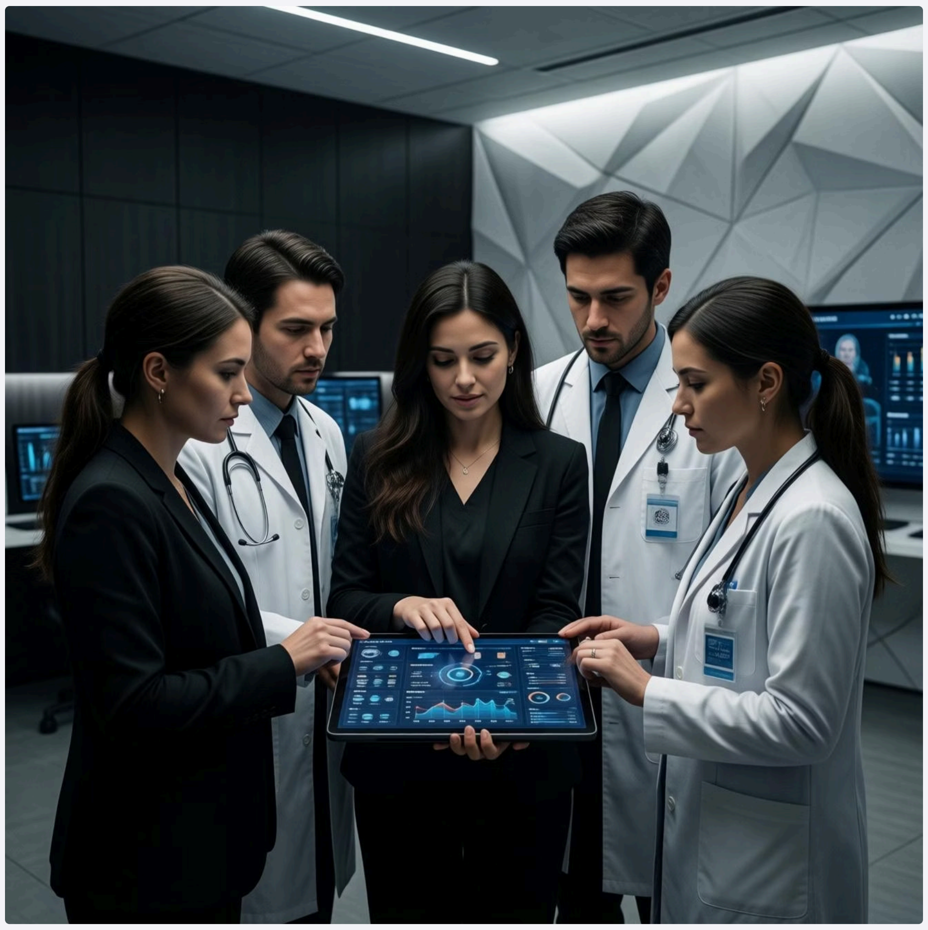
Prospective clinical trial of ML-guided decision support

03

Incorporate time-series physiological data and clinical notes

04

Implement explainable AI with SHAP values for transparency



> "These models offer potential for real-time implementation as clinical decision support tools to identify high-risk patients, guide resource allocation, and improve ICU outcomes."

Study Cohort: 25,324 ICU admissions | **Mortality Rate:** 9.86% | **Code Available:** Complete methodology documented and reproducible