

Predicting ICU Mortality Risk Using Machine Learning

Datathon 3

HAD7001H: Applied Machine Learning for Health Data Prof. Zahra Shakeri

Presented by:

Team 2

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Introduction

Dataset: MIT GOSSIS initiative, 91,000 observations

Key Features: Demographics, hospitalization factors, clinical & lab measures, and comorbidities.

Key Points:

- One-third of ICU-admitted adults die during hospitalization.
- Early prediction of mortality risk enables timely interventions and better resource allocation.
- Our study developed a model using data from the first 24 hours of ICU admission.
- The goal: Develop a predictive model to assist clinical decision-making.

ICU Mortality Prediction Process Flow Data Collection from ICU Admissions Feature Selection & Preprocessing **Model Training Mortality Prediction**

Data Engineering & Model Development

Feature Selection:

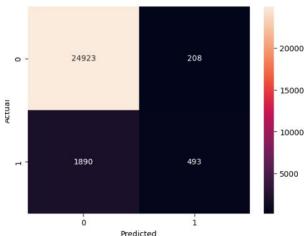
Clinical Expertise-Based Selection: Features were chosen based on clinical relevance, including demographics, hospitalization factors, clinical and lab measures, and comorbidities.

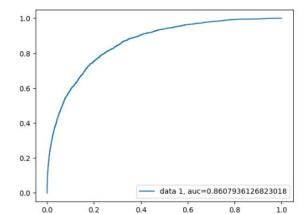
Handling Missing Data: Multiple imputations were applied

Modeling Approach:

- Neural network trained on 70% training and 30% testing split.
- Feature selection and hyperparameter tuning applied.
- Evaluation metrics: Accuracy, AUC-ROC, precision, recall, and f1-score.

Model	Accuracy	AUC-ROC	Precision (Class 1)	Recall (Class 1)
Neural Net	0.92	0.85	0.93	0.24
XGBoost	0.923	0.85	0.70	0.21





Key Findings & Future Directions

Findings:

- **Strong Overall Model Performance**: Neural network achieved 92% accuracy and an AUC-ROC of 0.85.
- Class Imbalance Issue:
 - \circ 91.4% survival, 8.6% mortality \rightarrow led to biased predictions.
 - High precision for survival cases (0.99 recall) but poor recall for mortality (0.24).
- Alternative Models (XGBoost) Improve Precision but Not Recall.

Future Improvements:

- Address class imbalance with oversampling/undersampling techniques.
- Explore cost-sensitive learning and ensemble models.
- Conduct external validation before clinical integration.

Closing: Our model effectively predicts survival but needs improvements to better identify high-risk patients.

Future iterations will focus on mitigating class imbalance and optimizing recall for better clinical utility.

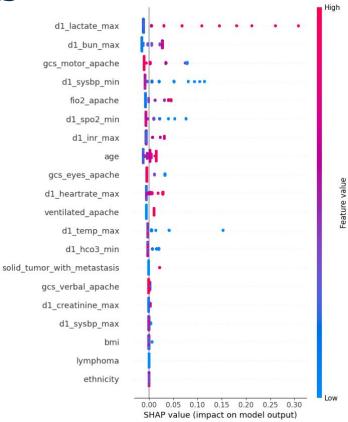


Fig. Feature importance analysis was performed using model evaluation metrics to identify the most relevant predictors for ICU mortality.