Predicting Acute Kidney Injury in Septic Patients Using Logistic Regression with MIMIC-III Data

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Master in Health Data Science — MHEDAS

January 23, 2025

Health
Co-funded by the European Union

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Introduction

- **Acute Kidney Injury (AKI):**
  - Sudden decline in kidney function.
  - Affects approximately 14% of hospitalized patients globally.
  - Higher prevalence in ICU.

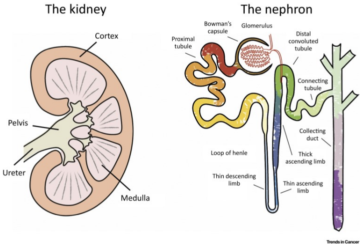

Figure: Kidney and nephron anatomy. Source: [1].

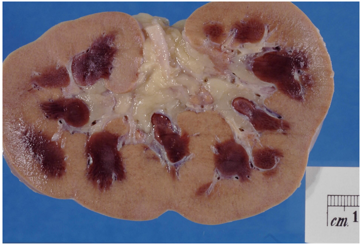

Figure: Kidney with AKI showing pale cortex and dark medullary tissue. Source: [2].

Cohort Building

Initial Cohort

`ICD9_CODE IN ('99591', '99592', '78552')`

Age: 18–89

LOS $\geq$ 48 hours

Gender, Ethnicity, Age

Comorbidities

Acute Kidney Injury (AKI), Chronic Kidney Disease (CKD), Coronary Artery Disease (CAD), Hypertension (HYP), Type 2 Diabetes Mellitus (DM2)

+

Laboratory Features

Albumin, Anion Gap, Bilirubin, Blood Urea Nitrogen (BUN), Chloride, Creatinine, estimated Glomerular Filtration Rate (eGFR), Glucose, Hematocrit, Hemoglobin, International Normalized Ratio (INR), Lactate, Partial Thromboplastin Time (PTT), Platelet Count, Potassium, Sodium

Chartevent Features

Diastolic Blood Pressure (DBP), Heart Rate (HR), Height, Oxygen Saturation (SpO2), Systolic Blood Pressure (SBP), Temperature, Weight

Mechanical Ventilation

Vasopressor Use

Column Mappings and eGFR Calculation

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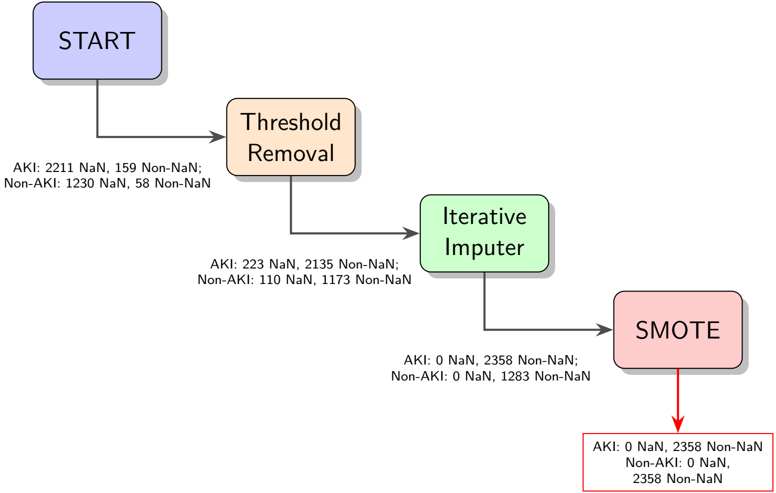
- Gender values = Male: **1**, Female: **0**.
- Ethnicities = **1**: Top1, **2**: Top2, **3**: Rest.
- All columns set to datatype **float** except for Gender, Ethnicities, and Comorbidities, which were **int**.
- eGFR calculated using a function provided in the **MIMIC-III GitHub** repository.
- Removed **Mechanical Ventilation** and **Vasopressor Use** columns as they were always 0 and provided no information.

```python
def egfr(creat: float, age: float, gender: int, ethnicity: float) -> float:
    """
    Calculate the estimated glomerular filtration rate (eGFR).

    Inputs:
        - creat (float): Creatinine level.
        - age (float): Age in years.
        - gender (int): Gender.
        - ethnicity (float): Ethnicity.

    Outputs:
        - float or None: The calculated eGFR value or none.
    """
    # Return None if inputs are not correct
    if pd.isnull(creat) or creat == 0.0 or age == 0.0:
        return None

    # Calculate eGFR
    factor_gender = 0.742 if gender == 0 else 1
    factor_ethnicity = 1.212 if ethnicity == 2 else 1
    eGFR = 175 * (creat**-1.154) * (age**-0.203) * factor_gender * factor_ethnicity

    return eGFR
```

Figure: eGFR function.

NaN Removal


START
Threshold Removal
Iterative Imputer
SMOTE
AKI: 2211 NaN, 159 Non-NaN;
Non-AKI: 1230 NaN, 58 Non-NaN
AKI: 223 NaN, 2135 Non-NaN;
Non-AKI: 110 NaN, 1173 Non-NaN
AKI: 0 NaN, 2358 Non-NaN;
Non-AKI: 0 NaN, 1283 Non-NaN
AKI: 0 NaN, 2358 Non-NaN
Non-AKI: 0 NaN,
2358 Non-NaN

Feature Selection

- Features were normalized to the range $[0, 1]$ using the Max-Min function:

$$X_{\text{scaled}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

- Variance Inflation Factor (VIF) was calculated for all features using the formula:

$$\text{VIF}_i = \frac{1}{1 - R_i^2}$$

- Features with VIF > 10 were removed iteratively. The process continued until all features had VIF < 10.
- The t-test was used to compare the means of quantitative features between the AKI and Non-AKI cohorts.
- χ^2-test to assess associations between categorical features and AKI status.

Feature Selection

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Table: Comparison of features between AKI and Non-AKI patients. Quantitative features are summarized by mean and standard deviation (SD), while categorical features are presented as counts for each group. A feature is considered statistically significant if the p-value is ≤ 0.05.

Feature (Unit)	AKI Mean (SD) / Count	Non-AKI Mean (SD) / Count	p-value
Age (years)	65.457 (14.986)	62.623 (15.045)	1.002×10^{-10}
Minimum Creatinine (mg/dL)	1.930 (1.513)	1.387 (1.753)	1.441×10^{-29}
Maximum Anion gap (mmol/L)	16.749 (4.605)	14.624 (3.604)	1.476×10^{-67}
Minimum Anion gap (mmol/L)	14.186 (3.753)	12.650 (3.070)	4.015×10^{-52}
Maximum Chloride (mmol/L)	108.420 (7.428)	107.488 (6.011)	2.234×10^{-6}
Minimum Chloride (mmol/L)	105.122 (7.557)	104.669 (5.856)	2.144×10^{-2}
Maximum Glucose (mg/dL)	174.921 (92.680)	155.957 (67.823)	1.341×10^{-15}
Maximum Platelet Count ($10^3/\mu L$)	225.550 (137.671)	237.127 (142.619)	4.588×10^{-3}
Maximum Potassium (mmol/L)	4.504 (0.822)	4.243 (0.683)	4.955×10^{-32}
Minimum Potassium (mmol/L)	3.862 (0.636)	3.707 (0.527)	1.777×10^{-19}
Maximum Sodium (mmol/L)	140.210 (6.018)	139.444 (4.198)	4.048×10^{-7}
Minimum Sodium (mmol/L)	137.386 (5.812)	137.058 (4.498)	3.030×10^{-2}
Minimum Hematocrit (%)	29.201 (5.483)	29.885 (4.839)	5.719×10^{-6}
Maximum Hemoglobin (g/dL)	10.647 (1.869)	10.867 (1.668)	2.086×10^{-5}
Minimum eGFR (mL/min/1.730 m^2)	54.405 (43.681)	97.813 (80.100)	5.736×10^{-112}
Minimum BUN (mg/dL)	39.019 (26.021)	20.502 (14.097)	2.487×10^{-185}
Minimum SBP (mmHg)	84.855 (14.873)	86.624 (13.538)	1.976×10^{-5}
Minimum DBP (mmHg)	41.174 (10.049)	42.601 (9.722)	7.452×10^{-7}
Maximum Temperature (°C)	37.611 (0.981)	37.858 (0.925)	7.728×10^{-19}
Minimum Temperature (°C)	36.077 (0.856)	36.221 (0.781)	1.383×10^{-9}
Gender	{0: 962, 1: 1396}	{0: 1172, 1: 1186}	9.689×10^{-10}
Ethnicity	{1: 1693, 2: 260, 3: 405}	{1: 1651, 2: 349, 3: 358}	2.707×10^{-4}
DM2	{0: 1382, 1: 976}	{0: 1597, 1: 761}	1.044×10^{-10}
CAD	{0: 1691, 1: 667}	{0: 1853, 1: 505}	5.794×10^{-8}
CKD	{0: 1593, 1: 765}	{0: 1972, 1: 386}	1.355×10^{-37}
HYP	{0: 1209, 1: 1149}	{0: 1451, 1: 907}	1.473×10^{-12}

Model Performance Metrics

Table: Performance metrics for training and testing datasets.

Metric	Train	Test
Accuracy	0.737	0.741
Precision	0.751	0.770
Recall	0.716	0.673
F1-score	0.733	0.718

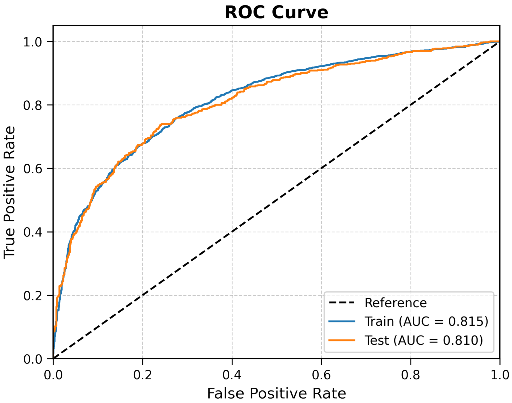

Figure: ROC curves for training and testing datasets.

Feature Contribution Analysis

- eGFR (most important marker for kidney function).
- Creatinine and BUN (indicators of renal health).
- Others: age, electrolytes, hemoglobin.

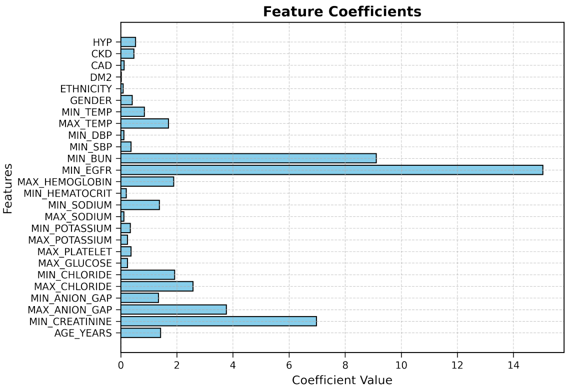

Figure: Feature importance in the logistic regression model.

Benchmarking Against Existing Studies

- Roknaldin et al. (2024): MIMIC-III database; 3301 ICU patients with sepsis; analyzed demographics, labs, vitals, and interventions. Multiple models.
- Malhotra et al. (2017): Multicenter dataset; 717 ICU patients; developed and validated an AKI risk score using logistic regression.
- Jiang et al. (2023): MIMIC-III database; 963 ICU patients with acute pancreatitis; developed a nomogram for AKI prediction using logistic regression.

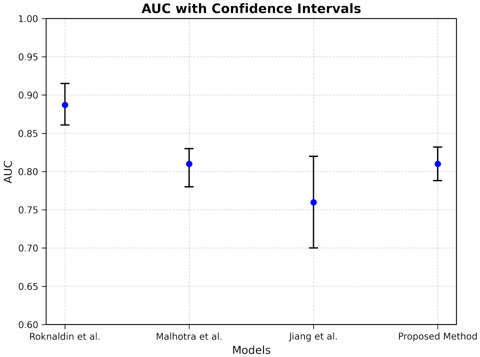

Figure: Comparison of AUC values across studies using logistic regression for AKI prediction.

Conclusions

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- **Study Findings:**
  - Developed a logistic regression model for AKI prediction.
  - Achieved AUC = 0.810 (95% CI: 0.788–0.832), accuracy = 74.06%, precision = 76.97%, recall = 67.34%, and F1-score = 71.83%.
  - Key predictors: eGFR, creatinine, BUN; secondary: age, electrolytes
- **Limitations:**
  - Single-source data limits generalizability.
  - Logistic regression may miss non-linear patterns.
  - Missing data imputation introduces uncertainty.
- **Future Directions:**
  - Add features like ICU interventions to improve accuracy.
  - Validate on external datasets for broader applicability.
  - Explore advanced models for capturing complex relationships.

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