BATCH-11

Real-Time Explainable-AI Based Interpretability for ICU Mortality Risk Prediction Using Electronic Health Records.

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INTRODUCTION

- Intensive Care Units (ICUs) are high-pressure environments where clinicians must make rapid, life-critical decisions.
- Predicting a patient's mortality risk at the right time can significantly improve treatment outcomes, resource allocation, and clinical planning.
- Electronic Health Records (EHRs) contain rich information—vital signs, demographics, lab values—but converting this complex, high-dimensional data into meaningful insights remains a challenge.
- While advanced machine learning models improve accuracy, their lack of transparency limits real-world adoption in clinical settings.
- To overcome these challenges, this study proposes a real-time, explainable AI framework for ICU mortality prediction using the MIMIC-III dataset. The system integrates LightGBM and XGBoost for high-performance prediction, combined with SHAP, LIME, and CAM to provide clear, interpretable explanations at both global and patient levels.
- A Kafka-based streaming pipeline simulates live patient data flow, enabling continuous, up-to-date risk assessment.

LITERATURE SURVEY

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RESEARCH GAPS

- High-performing models lack interpretability.
- Bias issues and limited generalization in single-center datasets.
- Limited real-time prediction frameworks.
- Heavy deep-learning models unsuitable for real-time deployment.
- Lack of clinician-friendly dashboards for actionable insights.
- Difficulty in integrating heterogeneous EHR data streams.

METHODOLOGY

VIEW

1. Dataset Description
Dataset: MIMIC-III (Electronic Health Records of ICU patients).
Target Variable: *hospital_death* (binary outcome).
Features Used:

- **Demographics:** Age, Gender, BMI, Ethnicity
- **ICU & Admission Details:** Admit source, ICU type, stay type
- **Clinical Variables:** Vital signs, lab measurements
- **Excluded:** Patient identifiers (encounter_id, patient_id, icu_id)

2. Data Preprocessing
Converted non-numeric entries to numeric values.
Handled missing values using **mean imputation**.
Applied **one-hot encoding** for categorical variables (drop_first to avoid multicollinearity).
Performed **80/20 stratified split** to maintain mortality class balance.
No scaling required since gradient-boosting models handle raw feature magnitudes.

METHODOLOGY

VIEW

3. Model Development

Machine learning models used:

- **LightGBM**, **XGBoost**

Chosen for:

- High performance on tabular medical data
- Ability to capture nonlinear interactions
- Natural handling of missing values

Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, ROC-AUC, Confusion Matrix.

Best performing model taken forward for real-time predictions & XAI.

4. Explainable AI (XAI) Integration

SHAP:

- Provides *global* and *local* feature importance.
- Shows which clinical features most influence mortality risk.

LIME:

- Generates patient-specific explanations.
- Helps clinicians understand the reasoning behind individual predictions.

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METHODOLOGY

VIEW

CAM (Class Activation Maps):

Used where applicable to visualize pattern influence for interpretability.

5. Real-Time Streaming Pipeline

A real-time data streaming pipeline **will be implemented** using **Apache Kafka** to simulate continuous ICU data flow.

A Kafka **producer will stream** new patient records as they arrive.

A Kafka **consumer will receive** the data, **apply preprocessing**, and **generate predictions** using the trained model.

XAI explanations using SHAP/LIME **will be integrated** into the pipeline.

The system **will aim** to produce predictions within milliseconds to support real-time ICU decision-making.

6. Dashboard Visualization

A clinician-friendly dashboard **will be developed** to display real-time mortality risk predictions.

The dashboard **will include**:

Patient-specific explanations for decision support

The dashboard **will be designed** to ensure high usability, visual clarity, and smooth integration into clinical workflows

SIGNIFICANCE OF PROPOSED STUDY

Provides interpretable ICU mortality predictions

- This study overcomes the limitations of black-box AI models by offering transparent explanations. Clinicians will be able to see *why* a prediction is made, not just the output.

Helps clinicians understand key risk factors using SHAP & LIME

- Explainable AI highlights the most influential clinical features behind each prediction. This improves clarity and helps clinicians validate the model's reasoning.

Supports faster, informed decision-making in ICUs

- The system aims to provide rapid mortality risk insights during critical situations. This enables timely interventions and better prioritization of high-risk patients.

Utilizes high-dimensional EHR data effectively

- The model transforms complex demographic, lab, and vital records into actionable insights. This ensures that the rich ICU data is fully leveraged for accurate predictions.

Lays the foundation for future real-time monitoring

- A streaming pipeline will eventually allow continuous patient risk assessment. This helps hospitals move toward proactive, real-time clinical decision support systems.

WORK PROGRESS TILL DATE

- **Dataset Preparation Completed**

The MIMIC-III dataset has been curated, cleaned, and structured for analysis.
All relevant demographic, clinical, and ICU-related features have been extracted.

• Data Preprocessing Pipeline Implemented

Non-numeric entries were converted, missing values were imputed, and categorical variables were one-hot encoded.
An 80/20 stratified split has been performed to preserve class balance.

• Machine Learning Models Built and Trained

LightGBM and XGBoost models have been successfully trained on the processed dataset.
Both models have shown strong performance across accuracy, recall, F1-score, and AUC metrics.

WORK PROGRESS TILL DATE

- **Model Evaluation and Comparison Completed**
Performance metrics and confusion matrix analysis have been generated for both models.
XGBoost currently shows the best recall and AUC, making it the stronger candidate for deployment.

- **Explainable AI Techniques Integrated**
SHAP has been applied for global and local feature importance visualization.
LIME has been used to generate patient-specific explanations for enhanced interpretability.

- **Initial Dashboard Development Started**
A basic dashboard structure has been designed to visualize predictions and SHAP contributions.
Work is in progress to refine the UI for a more clinician-friendly experience.

RESULTS AND DISCUSSION

Model Performance

- Both models show strong accuracy.
- XGBoost → best AUC & recall.
- Balanced sensitivity even under class imbalance.

Confusion Matrix Findings

- Good identification of both mortality and non-mortality cases.
- Reduced false negatives due to stratified sampling.
- **ROC Analysis**
- High AUC → strong class separability.

ROC Analysis

- High AUC → strong class separability.

Explainability

- SHAP: top features include age, BMI, ICU admission source, APACHE indicators, vital signs, lab parameters.
- LIME: detailed patient-specific risk explanations.

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THANK YOU