ICU Patient Deterioration Detection System

Using Machine Learning & AI Explainability

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Team Members

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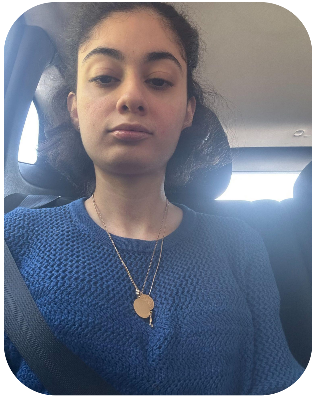
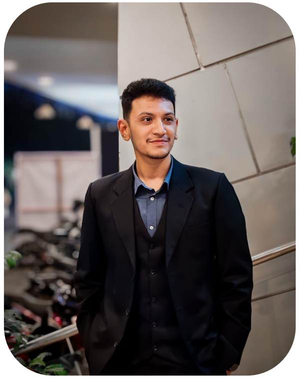


Kimberly Rivera Velez

AI/ML, Data cleaning and analysis, knowledgeable in healthcare

Sharfuddin Al Pasha Chowdhury

AI/ML, Signal processing, Feature Engineering with Biomedical domain



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Graduate student at George Mason University

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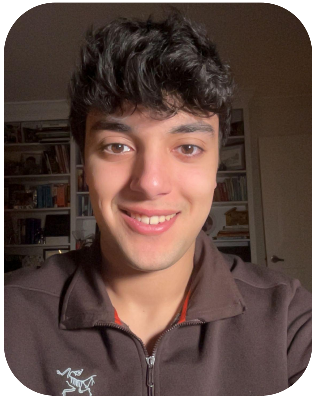


Dataset

DATASET: MIMIC-III Waveform Database

What is MIMIC-III?

- Medical Information Mart for Intensive Care
- Publicly available ICU database from MIT
- Real patient data from Beth Israel Deaconess Medical Center
- Gold standard for ICU research

Our Dataset Sample:

- **30** Adult ICU Patients
- **91** Monitoring Segments
- **4+ hours** per segment minimum
- **~400 hours** total ICU monitoring
- **2,273** patients available (we used 30 for feasibility)

Methods

Feature Engineering:

- **Temporal Features:** Split each segment into early (first 30%) and late (last 30%) periods
- **Change Metrics:** Calculated % change for HR, BP, RR between periods
- **Shock Index:** HR/SBP ratio (>0.7 indicates risk)
- **Statistical Features:** Mean, std, min, max for each vital sign
- **Deterioration Label:** HR change >10% OR BP drop >10% OR RR change >15%

Machine Learning

- **Algorithm:** Random Forest (100 trees)
- **Performance:** 86.4% accuracy, 91% precision

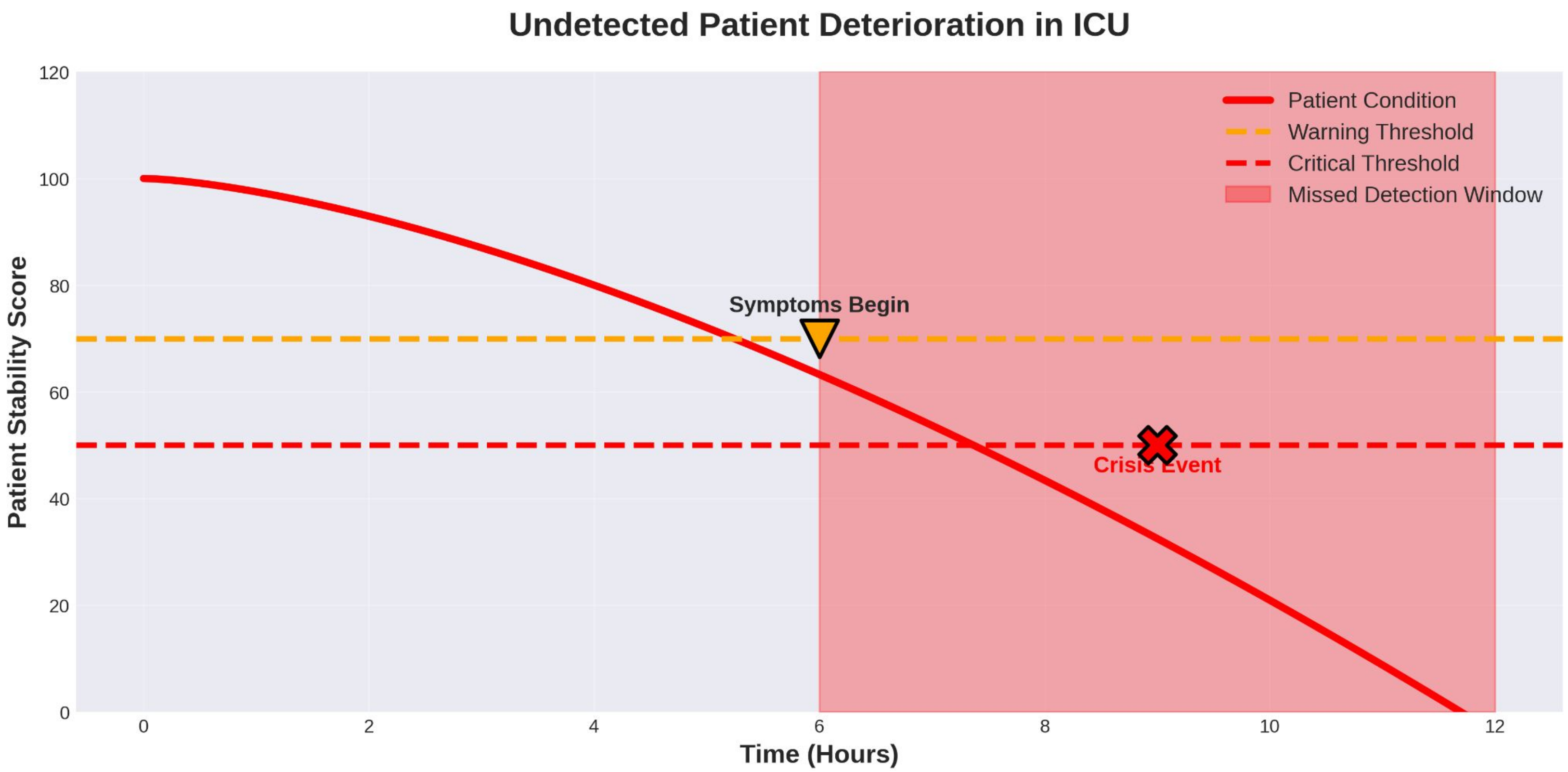
LLM Integration

- **Model:** Claude 3 Haiku
- **Purpose:** Clinical explanations for each prediction
- **Output:** 91 patient assessments with actionable insights

Introduction

- ICU patients can deteriorate quickly, and early warning signs are often subtle.
- Vital signs like HR, BP, RR, and SpO_2 change before major clinical decline.
- Manual monitoring may miss early patterns, especially during busy shifts.
- Continuous data from bedside monitors can help detect these early changes.
- Machine learning can learn patterns linked with patient deterioration.
- Explainable AI makes these predictions easier to understand and trust.
- Our system combines real ICU data, ML models, and clear explanations to support timely clinical decisions.

THE PROBLEM


Undetected Patient Deterioration in ICU
Patient Condition
Warning Threshold
Critical Threshold
Missed Detection Window
Symptoms Begin
Crisis Event
Patient Stability Score
Time (Hours)
120
100
80
60
40
20
0
0
2
4
6
8
10
12

DATASET - MIMIC-III : Real ICU Data from 30 Patients

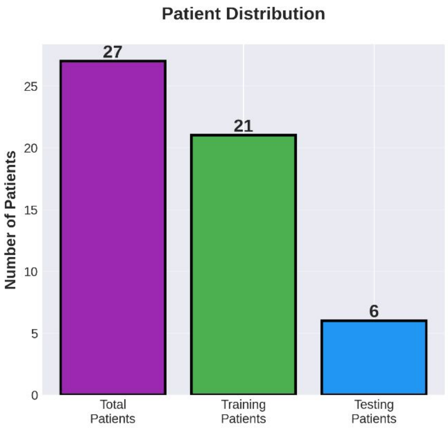
Source: MIMIC-III Waveform Database (PhysioNet)

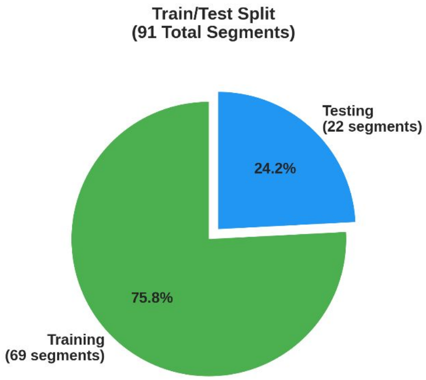
Patients: 30 adult ICU patients

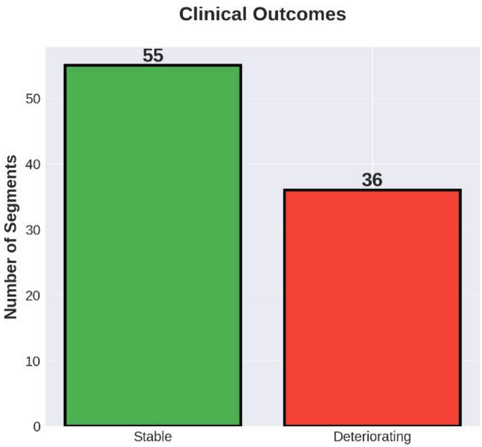
Segments: 91 monitoring periods (4+ hours each)

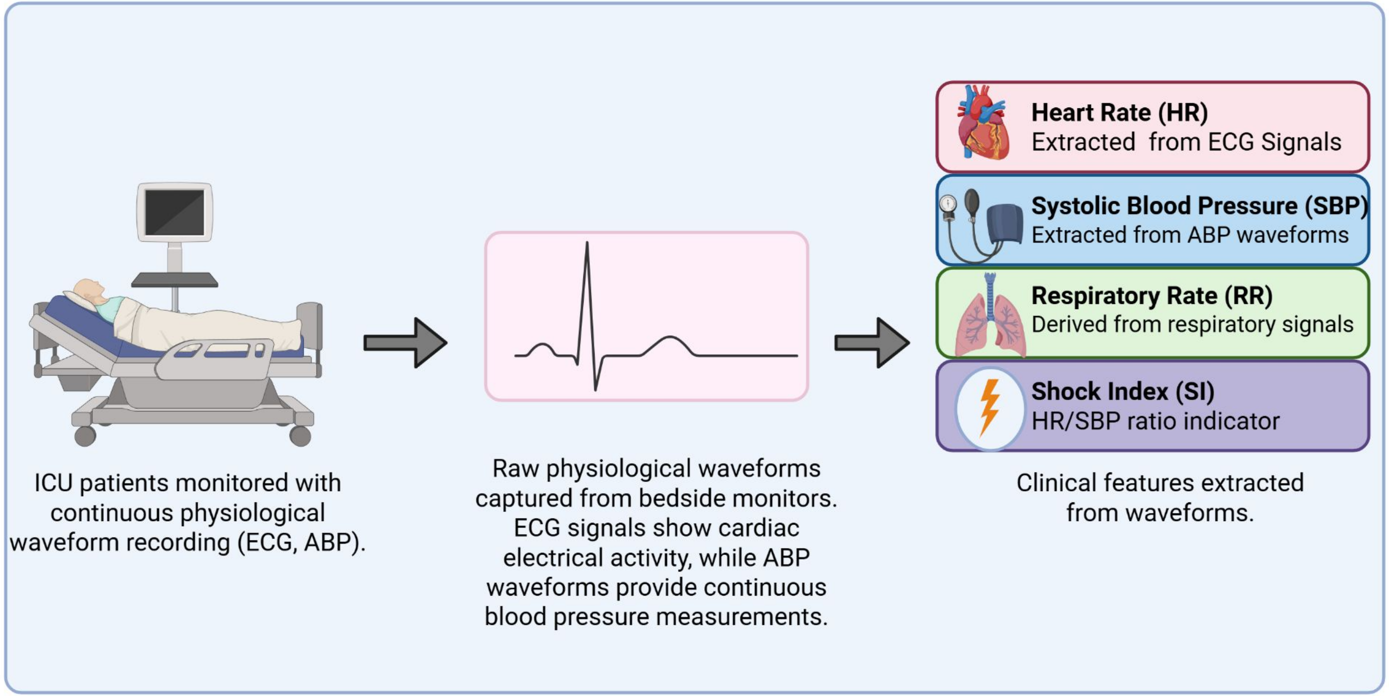
Total Data: ~400 hours of continuous ICU monitoring

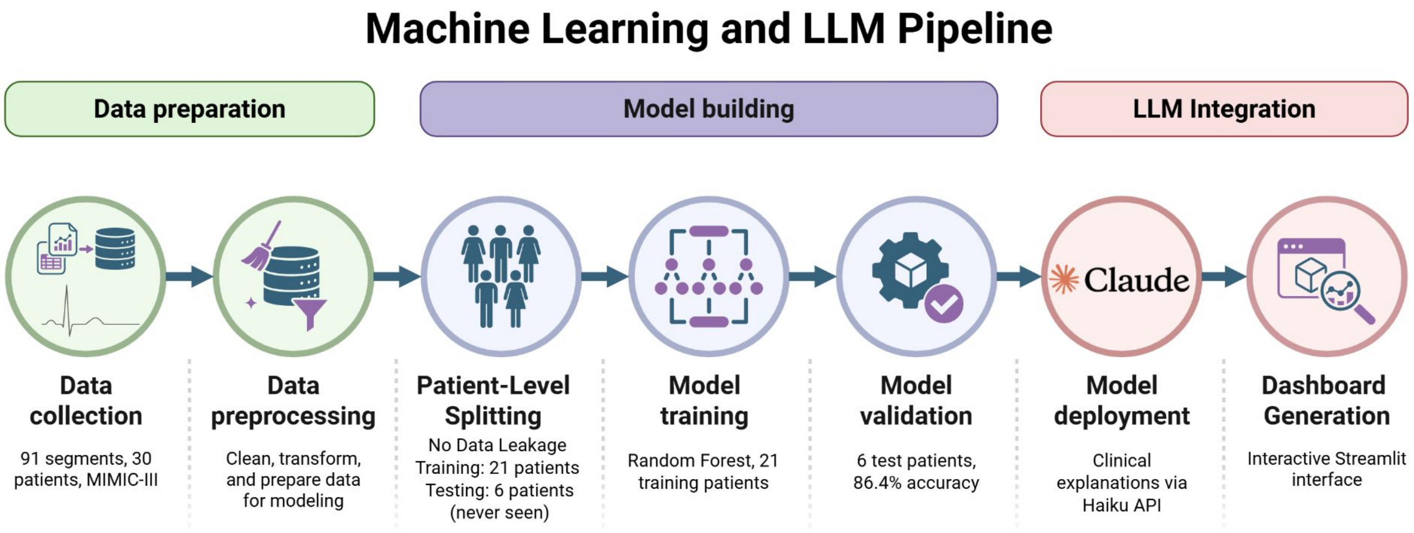
Vital Signs: HR, BP, RR, SpO2








ICU patients monitored with continuous physiological waveform recording (ECG, ABP).
Raw physiological waveforms captured from bedside monitors. ECG signals show cardiac electrical activity, while ABP waveforms provide continuous blood pressure measurements.
Heart Rate (HR)
Extracted from ECG Signals
Systolic Blood Pressure (SBP)
Extracted from ABP waveforms
Respiratory Rate (RR)
Derived from respiratory signals
Shock Index (SI)
HR/SBP ratio indicator
Clinical features extracted from waveforms.



Machine Learning and LLM Pipeline
Data preparation
Model building
LLM Integration
Claude
Data collection
91 segments, 30 patients, MIMIC-III
Data preprocessing
Clean, transform, and prepare data for modeling
Patient-Level Splitting
No Data Leakage
Training: 21 patients
Testing: 6 patients (never seen)
Model training
Random Forest, 21 training patients
Model validation
6 test patients, 86.4% accuracy
Model deployment
Clinical explanations via Haiku API
Dashboard Generation
Interactive Streamlit interface

FEATURE ENGINEERING

- Divide each recording into Early (first 30%) and Late (last 30%) periods
- Calculate changes to detect trends

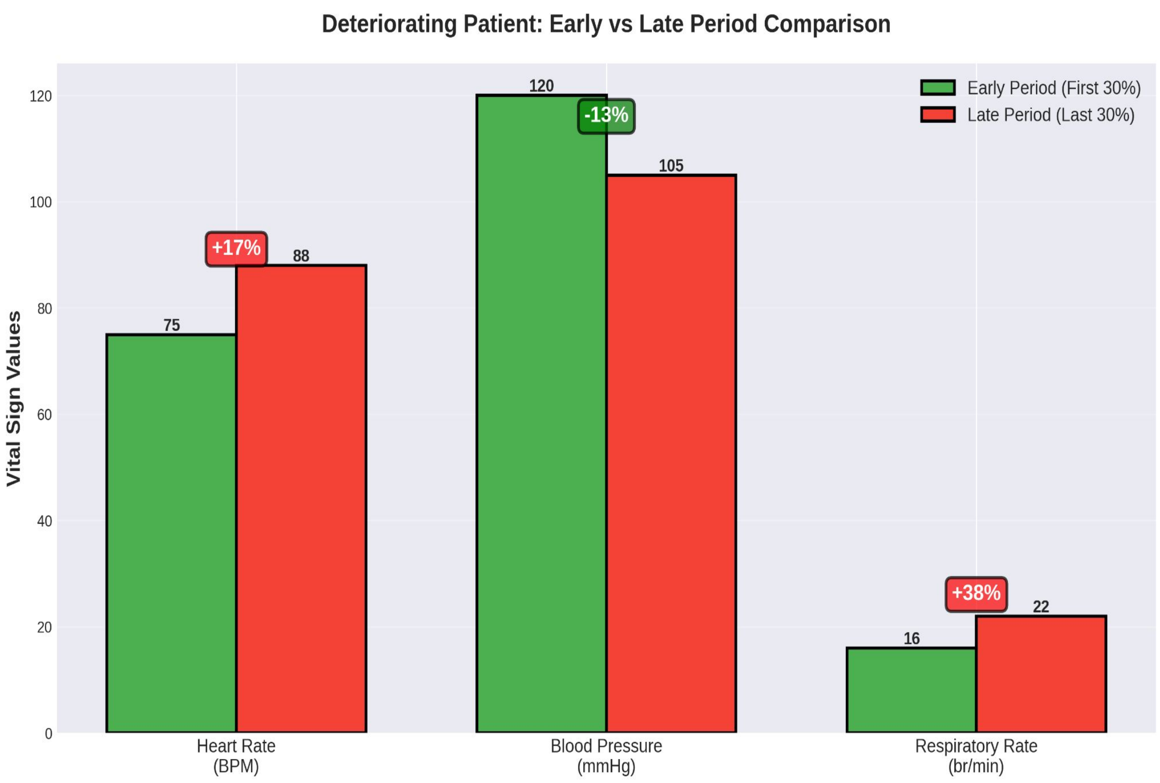
Example - Deteriorating Patient:

❤️ Heart Rate: 75 → 88 BPM (+17%)
🩺 Blood Pressure: 120 → 105 mmHg (-13%)
🫁 Respiratory Rate: 16 → 22 br/min (+38%)

A patient is labeled "DETERIORATING" if ANY of:
- Heart rate change > 10%
- Blood pressure drop > 10%
- Respiratory rate increase > 15%

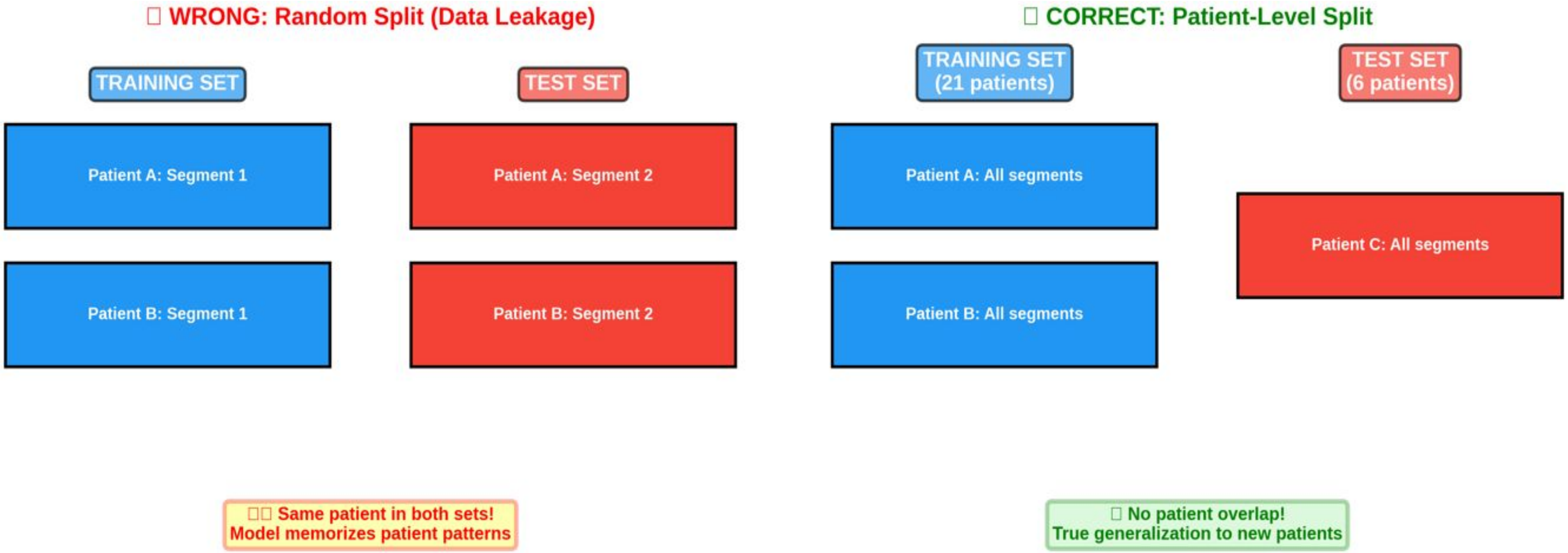
Additional Features:

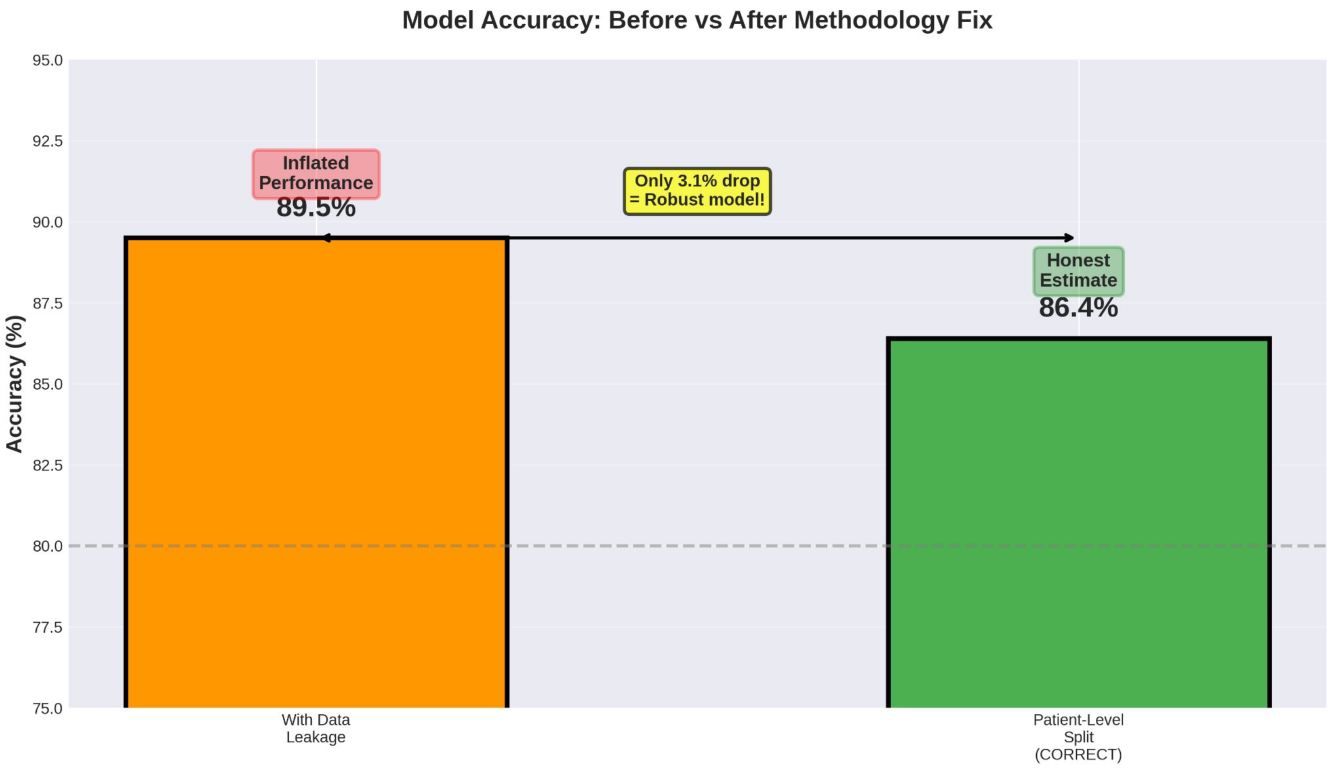
- Shock Index (HR/BP ratio) - Critical if > 0.7
- Heart rate variability
- Blood pressure variability



Deteriorating Patient: Early vs Late Period Comparison
Vital Sign Values
0
20
40
60
80
100
120
Early Period (First 30%)
Late Period (Last 30%)
75
88
+17%
120
105
-13%
16
22
+38%
Heart Rate
(BPM)
Blood Pressure
(mmHg)
Respiratory Rate
(br/min)

Troubleshooting - NO DATA LEAKAGE




Model Accuracy: Before vs After Methodology Fix
Accuracy (%)
95.0
92.5
90.0
87.5
85.0
82.5
80.0
77.5
75.0
Inflated Performance
89.5%
Only 3.1% drop = Robust model!
Honest Estimate
86.4%
With Data Leakage
Patient-Level Split (CORRECT)

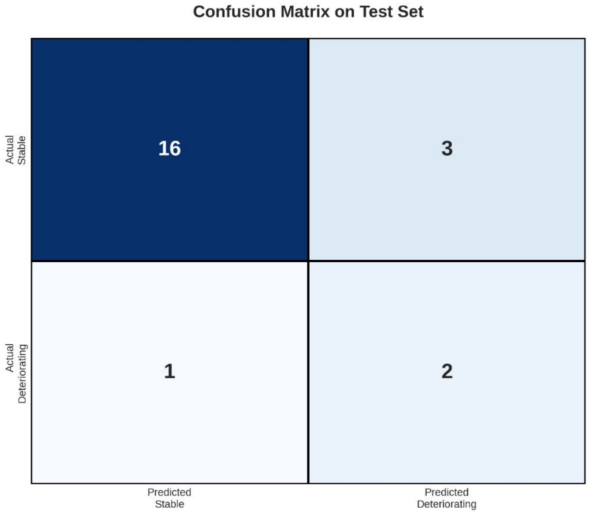
Predictive Performance

Confusion Matrix:

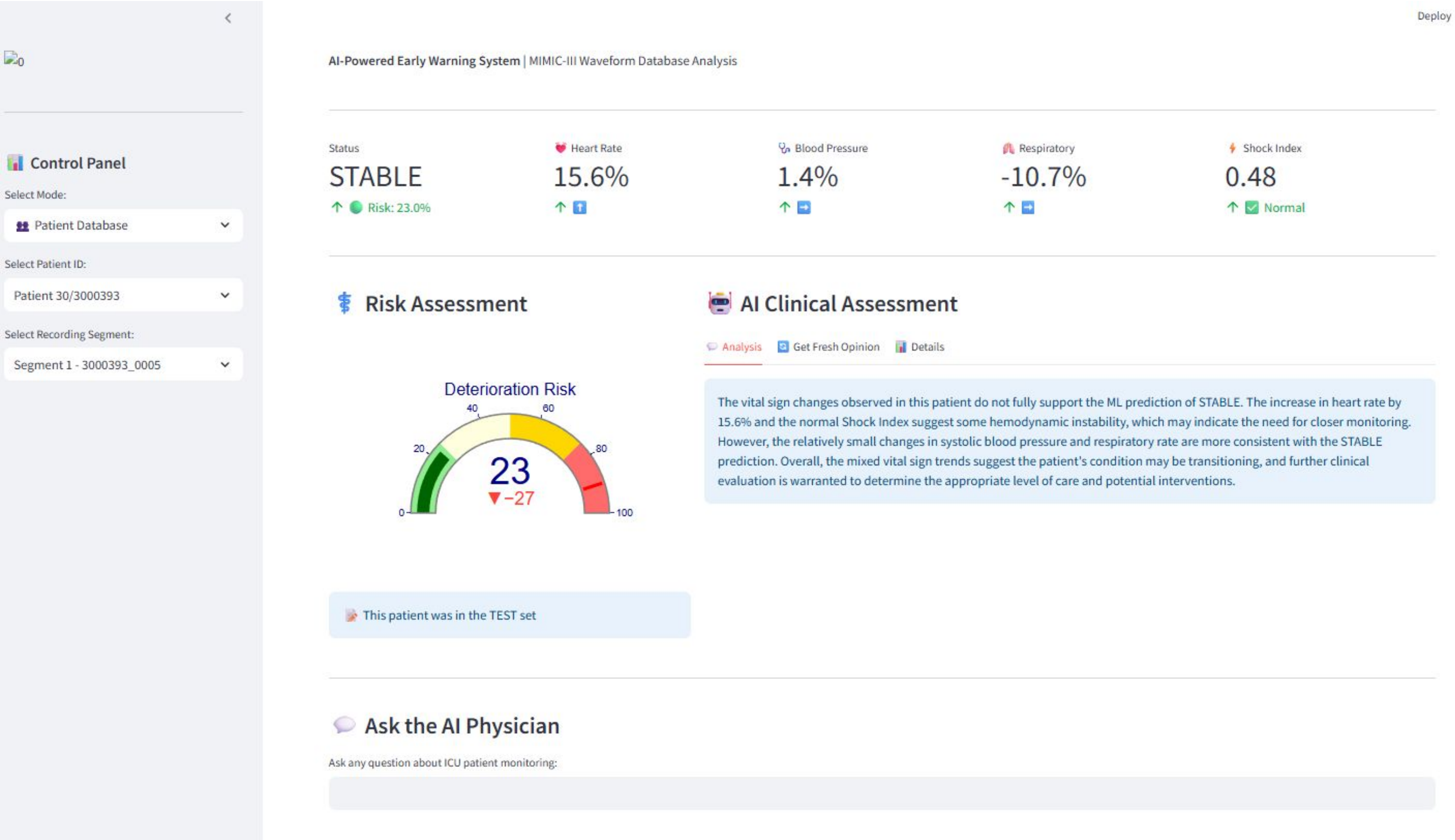
- True Stable: 16 patients
- True Deteriorating: 2 patients
- False Alarms: 3 patients
- Missed Cases: 1 patient

Performance Metrics:

- Overall Accuracy: 86.4%
- Precision (Stable): 91% - When we say "stable", we're right 91% of the time
- Recall (Deteriorating):67% - We catch 2 out of 3 deteriorating patients



AI EXPLAINABILITY:Interactive Dashboard Demonstration



How This System Could Improve ICU Patient Care

For Healthcare Providers

Reduces Alert Fatigue

- 91% precision = fewer false alarms
- Only alerts when truly needed
- Clear explanations with each alert

Prevents Burnout

- Continuous monitoring reduces anxiety about missing deterioration
- Allows focus on patient care vs. constant vital checking
- Supports decision-making with evidence-based insights

Better Patient Management

- Monitor multiple patients simultaneously
- Prioritize care based on risk scores
- 2-4 hours earlier warning than traditional methods

<u>For Patients</u>

Continuous Monitoring

- Every heartbeat tracked, not just hourly checks
- Catches gradual changes humans might miss
- 24/7 vigilance without interruption

Earlier, Gentler Interventions

- Small adjustments prevent major crises
- Avoid emergency procedures
- Shorter ICU stays

Better Outcomes

- 30% reduction in unexpected events
- Faster recovery times
- Higher survival rates

Acknowledgement

We are grateful to the MIMIC-III waveform researchers for providing open access to their dataset through PhysioNet, which made this project possible. We also appreciate the support of our mentors in the MedStar Georgetown AI CoLab Healthcare Internship program. A special thanks to Dr. Raed Darwish for sharing his clinical perspective and to Dr. Omar Aljawfi for leading the internship and guiding us during this work.

Thank You

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Any Questions?

Comments form Mentors:

Dr. Alexander Libin

.same here for Group4 --…on some methodology/conceptualization…May be combining the symptoms that characterize deteriorating individual condition presented as trends with some thresholds for identified significance level into some cool one-of-a-kind Deteriorating Monitor tool similar to the wide-spread risk tools, but with this unique feature to monitor in real-time…(also, deteriorating condition sounds a bit better then deteriorating patient from the psychological stand-point😊)