Patient Deterioration Risk Prediction

Project Overview:

This project focuses on predicting the risk of patient deterioration in hospital settings using machine learning. By analyzing vital signs and laboratory measurements, the model classifies patients into either deterioration or no deterioration, enabling early clinical intervention and improving patient safety and outcomes.

In clinical settings, the ability to predict a patient's physiological decline before it becomes critical is life-saving. This project focuses on building a predictive analytics system that monitors hourly patient data to forecast potential deterioration within a 12-hour window. The primary objective is False Negative (FN) Reduction, ensuring that no high-risk patient is overlooked by the system, even if it leads to a slightly higher rate of false alarms (False Positives).

Dataset:

The model utilizes a "Panel Data" format (longitudinal data), where each row represents one hour of a patient's stay.

- **File Name: `hospital_deterioration_hourly_panel.csv`**
- **Total Records: 2,000 hourly observations.**
- **Key Feature Categories:**
    - **Vital Signs: `heart_rate`, `respiratory_rate`, `spo2_pct` (Oxygen saturation), `temperature_c`, `systolic_bp`, `diastolic_bp`.**
    - **Laboratory Results: `wbc_count` (White Blood Cells), `lactate`, `creatinine`, `crp_level` (C-Reactive Protein), `hemoglobin`.**
    - **Clinical Intervention: `oxygen_flow`, `oxygen_device`, `nurse_alert`, `mobility_score`.**
    - **Demographics: `age`, `gender`, `comorbidity_index`.**
    - **Target Variable: `deterioration_next_12h` (Binary: 1 if deterioration occurs in the next 12 hours, 0 otherwise).**

The label is **not taken directly from a single column**, but is generated using a **rule-based clinical deterioration function**.

Data Preprocessing & Engineering

Before feeding the data into the models, several critical steps were taken to ensure data integrity:

1. **Imputation:** While the current dataset is complete, the pipeline includes `SimpleImputer` using the **mean** strategy to handle any future missing medical values.
2. **Encoding:** Categorical variables such as `gender`, `admission_type`, and `oxygen_device` were converted into numerical format using **One-Hot Encoding**.
3. **Class Imbalance Handling:** In medical datasets, the "Deterioration" event is much rarer than "Stable" states. To prevent the model from simply guessing "Stable" every time, we calculated **Class Weights** to penalize the model more heavily when it misses a positive case (deterioration).

Modeling Strategies

To effectively predict patient deterioration and minimize the risk of missed critical cases, two complementary modeling strategies were implemented and evaluated.

Strategy A: Multi-Layer Perceptron (Neural Network)

The Neural Network approach was employed to capture complex and non-linear relationships among patients' vital signs and clinical measurements.

- **Architecture:**
  A deep learning model based on a **Multi-Layer Perceptron (MLP)** architecture.

- **Network Structure:**
  The model consists of:

  - An input layer representing patient features,

  - One or more hidden layers with **64 neurons** using ReLU activation,

  - A final **Sigmoid output layer** for binary classification.

- **Optimization Method:**
  Training was performed using **Stochastic Gradient Descent** optimized with the **Adam optimizer**, ensuring efficient convergence.

- **Medical Objective:**
  The model was specifically tuned to **maximize Recall**, prioritizing the detection of deteriorating patients. This strategy minimizes **False Negatives**, which is critical in

clinical settings where missing a high-risk patient could have severe consequences.

Strategy B: Random Forest (Ensemble Learning)

The Random Forest model was implemented as a robust and interpretable alternative, particularly suited for handling noisy and heterogeneous medical data.

- **Model Configuration:**
  An ensemble of **300 decision trees** (`n_estimators = 300`) was used to enhance prediction stability and performance.

- **Class Imbalance Handling:**
  The model applies `class_weight = 'balanced'` or `balanced_subsample` to address the natural imbalance in medical deterioration datasets.

- **Key Advantage:**
  Random Forest provides **feature importance analysis**, allowing clinicians and researchers to identify the most influential predictors of patient decline, such as **lactate levels**, **heart rate**, and other vital signs. This enhances model interpretability and clinical trust.

Summary

Both models were designed with a strong clinical focus:

- The **Neural Network** excels at capturing complex patterns and maximizing Recall.

- The **Random Forest** offers robustness, interpretability, and insight into critical medical features.

Together, these strategies provide a balanced and reliable framework for patient deterioration prediction.

Performance Evaluation (Medical Context)

In medical prediction systems, conventional evaluation metrics such as **accuracy** are often misleading, particularly in imbalanced datasets where critical conditions occur less frequently. Therefore, accuracy was not considered a reliable performance indicator for this project. Instead, the evaluation focused on clinically meaningful metrics that directly impact patient safety.

Key Evaluation Metrics

Recall (Sensitivity)

Recall measures the proportion of actual patient deterioration cases that are correctly identified by the model.

- **High Recall = High Patient Safety**
- A higher recall ensures that most deteriorating patients are detected early, enabling timely medical intervention.
- This metric was prioritized to minimize the risk of undetected clinical decline.

Confusion Matrix Analysis

The confusion matrix was used as a core diagnostic tool to understand model behavior in a clinical setting:

- **True Positives (TP):**
  Patients whose deterioration was correctly detected, allowing early intervention and potentially preventing severe outcomes.
- **False Negatives (FN):**
  The most critical error type in this application. These represent patients who experienced deterioration but were not flagged by the model.
  Reducing False Negatives was the primary objective, with the goal of driving this number as close to zero as possible.

F1-Score

While maximizing Recall is essential, excessive sensitivity can lead to an overwhelming number of false alarms.

- The **F1-score** was used to balance **Recall** and **Precision**.
- This ensures that the model remains clinically usable by avoiding an excessive number of **False Positives**, which can cause **alarm fatigue** among healthcare professionals.

Prediction:

New patient data can be fed into the model as a dictionary of characteristic values.

The input data is measured using the same StandardScaler used in the training data.

The model predicts the probabilities of each deterioration category, and the category with the highest probability is selected.

The predicted category is then associated with an easy-to-read label: Deterioration, No Deterioration

Conclusion

This project demonstrated the effectiveness of machine learning models in predicting patient deterioration using clinical and vital sign data, with a strong emphasis on **patient safety**. Rather than relying on accuracy, the models were optimized to **maximize Recall** and minimize **False Negatives**, as missing a deteriorating patient represents a critical clinical risk.

Both the Neural Network and Random Forest models showed promising performance. The Neural Network captured complex non-linear patterns, while the Random Forest provided robustness and interpretability through feature importance analysis. Threshold tuning and confusion matrix analysis played a key role in reducing missed critical cases while maintaining practical usability.

Overall, the results highlight the potential of machine learning as a supportive tool for early clinical intervention, contributing to improved patient outcomes and safer healthcare decision-making.