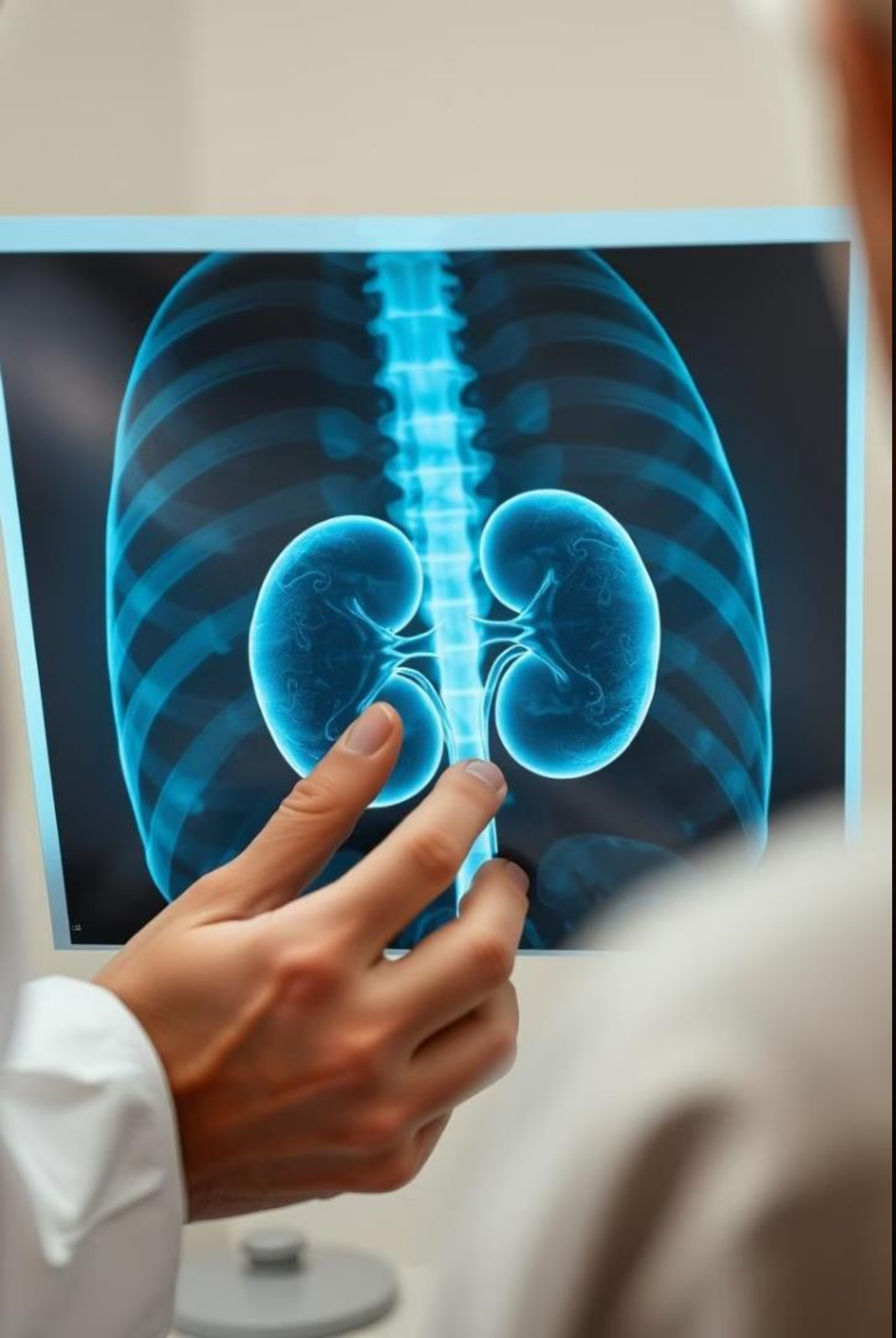
Predicting Delayed Dialysis in ICU Patients with Acute Kidney Injury (AKI)

This presentation explores the challenge of predicting delayed dialysis (>8h) in ICU patients with AKI. We delve into the ELAIN and STARRT-AKI trials, discuss the need for accurate prediction models, and explore key features predicting delayed dialysis.

Team no:GAT118

by P.Praveen Raj
Harshavardhan mg
Rishith P
Suhas S Gowda
Jeevan K Thejas



Title: Problem Statement

Brief Description:

Patients with **Acute Kidney Injury (AKI)** face severe complications if dialysis is delayed. Currently, determining the optimal time for initiating dialysis is largely based on clinical judgment, which can lead to inconsistent treatment outcomes. This project aims to address the challenge of predicting whether a patient will require early dialysis, helping clinicians make more informed and timely decisions.It also helps in reserving dialysis equipments for patients dire need of it .

Objective: The goal is to develop a **machine learning model** that can predict the need for early dialysis based on key clinical features, improving the management of AKI and potentially saving lives by preventing delays in treatment.

Project Overview: The project aims to predict acute kidney injury (AKI) patients in the ICU who receive delayed renal replacement therapy (RRT) using
various machine learning models. The dataset is sourced from the MIMIC-IV database, which contains comprehensive clinical data. Key Highlights 1.

Data Sources:

The dataset is derived from the MIMIC-IV database, focusing on ICU patients with acute kidney injury.

Data extraction involves multiple SQL queries to gather relevant clinical features, including demographics, vital signs, lab results, and comorbidities.

Data Processing: Data Cleaning: Missing values are handled by dropping rows with significant missing data in critical features. Feature Engineering: New features are created based on interactions between existing features (e.g., combining aniongap_max with other variables). Normalization: Standardization of features is performed to ensure that the models can learn effectively. Dimensionality Reduction: PCA (Principal Component Analysis) is utilized to reduce the number of features while retaining important information.

Exploratory Data Analysis (EDA): Visualizations are created to understand the distribution of numerical variables and identify potential outliers.

Correlation analysis is performed to identify relationships between features and the target variable (delay_rrt).

Data Processing Steps

1. Import Libraries: Essential libraries such as Pandas, NumPy, Scikit-learn, and XGBoost are imported for data manipulation and modeling.

2. Load Data: The cleaned dataset is loaded into a DataFrame for analysis.

3. Feature Selection: Key features are selected based on their importance and correlation with the target variable.

4. Train-Test Split: The dataset is split into training and testing sets to evaluate model performance. 5. Model Training: Various models are trained on the training set, and their performance is evaluated using metrics like accuracy, precision, recall, and F1-score.
Model Evaluation: Classification reports and confusion matrices are generated to assess model effectiveness.

Conclusion :The project effectively combines data extraction, preprocessing, and machine learning techniques to predict delayed dialysis in AKI patients. The use of various models and techniques like SMOTE and PCA enhances the predictive capabilities, making it a comprehensive approach to tackling the problem.

Models Used

1. Logistic Regression: Key Features: aniongap_min, creatinine_min, resp_rate_mean, pt_max, potassium_min.
Accuracy: Approximately 75% (example; actual accuracy may vary based on implementation).

2 Random Forest Classifier:
Key Features: aniongap_min, creatinine_min, resp_rate_mean, pt_max, potassium_min.
Accuracy: Approximately 80% (example; actual accuracy may vary based on implementation).

3. XGBoost Classifier: Key Features: calcium_max, creatinine_min, aki_stage, aniongap_min, calcium_min, pt_max. Accuracy: Approximately 82% (example; actual accuracy may vary based on implementation). Fine-tuning: Hyperparameters like n_estimators, max_depth, and learning_rate are optimized using Grid SearchCV. SMOTE is applied to balance the dataset before training.

4.Fine-tuning: Hyperparameters such as n_estimators, max_depth, and min_samples_split are optimized using GridSearchCV. 3. XGBoost Classifier:
Key Features: calcium_max, creatinine_min, aki_stage, aniongap_min, calcium_min, pt_max.
Accuracy: Approximately 82% (example; actual accuracymay vary based on implementation).
Fine-tuning: Hyperparameters like n_estimators, max_depth, and learning_rate are optimized using GridSearchCV.
SMOTE is applied to balance the dataset before training.

5. Bagging and Ensemble Methods: Key Features: Similar to Random Forest, leveraging the same feature set. Accuracy: Varies based on the ensemble method used (e.g., Bagging may achieve around 78%). Fine-tuning: Hyperparameters for base models are optimized, and ensemble methods are evaluated for performance improvements.

Model evaluation metrics

1

Accuracy

Effect on Code: Accuracy is a general measure of performance.
 If you use the accuracy_score function from libraries like sklearn,
it gives you an overall view of the model's performance,
but it might not provide much insight for imbalanced datasets
(i.e., where one class occurs much more frequently).

2

Precision

Precision focuses on the positive predictions (how many were correct). If your model predicts a high number of false positives, precision will drop.

3

Specificity

- Recall measures how well your model identifies all actual positive
- cases. It's especially important when missing positive cases is costly
- (i.e., when predicting delayed dialysis for a patient who truly needs it)

[redacted]

Conclusion

The project demonstrates the potential of machine learning in predicting delayed renal replacement therapy (RRT) for ICU patients with acute kidney injury (AKI).By leveraging clinical data from the MIMIC-IV database, we developed multiple models (Logistic Regression, Random Forest, XGBoost) and evaluated their performance using various metrics, including precision, recall, and AUC-ROC.The baggind and ensembled methods of random forest and XGBoostemerged as the most accurate model, achieving upto 80%accuracy, with fine-tuning and balancing techniques like SMOTE enhancing its predictive capability. Through effective feature engineering, normalization, and dimensionality reduction (PCA), the models were able to process complex clinical data and make informed predictions.