Antibiotic Dosage prediction based on Vitals

Student Name: Vishal Kumar Maurya
Roll Number: 2022580

BTP report submitted in partial fulfillment of the requirements
for the Degree of B.Tech. in Computer Science & Engineering

on ...23rd April 2025...

BTP Track: Research track

BTP Advisor
Dr. Tav Pritesh Sethi

Indraprastha Institute of Information
Technology New Delhi

Student's Declaration

I hereby declare that the work presented in the report entitled **"...Prediction of antibiotic dosage based on vitals..."** submitted by me for the partial fulfillment of the requirements for the degree of *Bachelor of Technology* in *Computer Science & Engineering* at Indraprastha Institute of Information Technology, Delhi, is an authentic record of my work carried out under guidance of **..**Dr. Tav Pritesh Sethi**...** Due acknowledgements have been given in the report to all material used. This work has not been submitted anywhere else for the reward of any other degree.

..... **Place & Date: .....**

...(Vishal Kumar Maurya)...

Certificate

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

..... **Place & Date: .....**

..(Dr. Tav Pritesh Sethi**)..**

Abstract

In critical care environments, the timely and accurate adjustment of antibiotic dosage is crucial for ensuring effective treatment outcomes, minimizing recovery times, and preventing the development of antibiotic resistance. Inappropriate antibiotic dosing can lead to ineffective treatment, adverse drug reactions, or the emergence of resistant bacterial strains, which pose serious risks to patient safety and public health. This project proposes a machine learning-based system that predicts whether the dosage of an antibiotic should be increased or decreased, based on trends observed in patient vital signs.

The system leverages time-series data of patient vitals recorded at six-hour intervals over a 24-hour period, effectively capturing the body's physiological responses following antibiotic administration. Key parameters such as heart rate, respiratory rate, blood pressure, and oxygen saturation are monitored to assess how the patient is reacting to the treatment. By analyzing the trajectory of these clinical indicators, the model learns to detect patterns that signal the need for dosage adjustment, allowing for personalized and adaptive treatment decisions.

Our approach integrates medical knowledge with advanced data-driven techniques to provide a real-time decision support tool for clinicians. This tool is designed to augment clinical judgment, enabling healthcare professionals to make informed, dynamic antibiotic dosing decisions based on individual patient responses rather than relying solely on static protocols. Through this system, we aim to enhance the precision of care, reduce the risks of over- or under-treatment, and contribute to the global effort of antimicrobial stewardship.

Ultimately, the proposed model has the potential to improve patient outcomes in intensive care settings by providing proactive and personalized recommendations.

Keywords : Antibiotic dosage adjustment, Machine learning, Patient vitals, Time-series data, Clinical decision support, Personalized medicine, Antimicrobial stewardship, Critical care, Predictive modeling, Vital sign analysis, Adaptive treatment, Healthcare AI, Dynamic dosage prediction, Real-time monitoring, Intelligent healthcare systems

Week	Chapters	Task Description
1-3	Chapter 4	Research on drowsiness detection and review of prior work.
4	Chapter 1	Introduction to vitals-to-antibiotics research direction.
5-6	Chapter 3	Dataset correction and initial exploratory data analysis (EDA).
7	Chapter 3	Matching patient dataset with prescription dataset.
8	Chapter 3	Final dataset creation and analysis.
9-10	Chapter 3	Applying model on complete dataset (all days).
11	Chapter 3	Rectifying and refining the dataset structure.
12-13	Chapter 3	Complete EDA and model training.

Contents

Chapter 1

Introduction

1. Preparatory Work for the Study

In preparation for this study, a comprehensive dataset was curated, containing information on antibiotic administration across various patients. Each data record includes key clinical and pharmacological variables such as drug name, dosage, route of administration, antibiotic category, and vital signs measured at multiple time intervals (e.g., at start, after 6 hours, 12 hours, etc.)

A major preprocessing step involved transforming complex stringified list formats into structured, row-wise data where each drug administration instance could be analyzed independently. Additional parsing was applied to handle non-standard dosage values (e.g., ranges or undefined entries), and derived features were engineered to capture meaningful relationships between treatment variables and patient responses.

This preparatory work was essential to enable robust modeling and analysis of dosage dynamics, setting the foundation for predictive modeling of antibiotic dosage adjustments based on temporal changes in patient vitals.

2. Objectives

The key aim of this study is to build a predictive model that uses historical antibiotic administration data and corresponding patient vitals to support clinical decision-making. The specific objectives are:

- **To predict whether an antibiotic dose should be increased, decreased,** based on the patient's early physiological response.
- **To extract meaningful patterns between drug properties (e.g., type, route, dose) and changes in patient vitals** over the first few hours of administration.
- **To enable automated, data-driven recommendations for dose adjustments** that can improve the personalization of antibiotic therapy.
- **To create a model that handles real-world clinical data complexity**, such as co-administration of multiple antibiotics, irregular dosage formats, and missing or

uncertain values.

- **To provide a framework for integrating AI into ICU workflows**, enhancing the efficiency and accuracy of antibiotic dosing decisions.

Access to Complete Project Files

The complete implementation code, dataset preprocessing steps, model training notebooks, and results are available at the following link:

Click here to access the full project on Google Drive

References

1. Research paper 1
2. Research paper 2

Chapter 2

Related Work

The integration of machine learning (ML) into clinical decision-making, particularly in antibiotic stewardship within intensive care units (ICUs), has garnered significant attention. Two notable studies exemplify this progression:

1. Predicting Appropriateness of Empiric Antibiotic Therapy

Goldschmidt et al. (2025) developed a machine learning model aimed at predicting the appropriateness of empiric antibiotic treatments for ICU-acquired bloodstream infections. Utilizing the MIMIC-III database, the study addressed challenges such as missing data and dataset imbalances through innovative computational methods. The model achieved an AUROC of 77.3% and an AUPRC of 40.4% on validation datasets. Notably, external validations using MIMIC-IV and data from Rambam Hospital demonstrated consistent performance, underscoring the model's generalizability. Furthermore, the model's ability to predict mortality risk highlighted its potential utility in clinical settings, identifying a 30% mortality rate in high-risk patients compared to 16.8% in low-risk groups.

2. Machine Learning for Predicting Inappropriate Empiric Antibiotic Treatment

In a separate study, researchers developed a machine learning model to predict the appropriateness of empiric antibiotics for ICU-acquired bloodstream infections. The model utilized data from the MIMIC-III database and addressed issues like missing values and dataset imbalances with novel computational techniques. Achieving an AUROC of 77.3% and an AUPRC of 40.4% on validation, the model's robustness was further confirmed through external validations on MIMIC-IV and data from Rambam Hospital. Additionally, the model effectively predicted mortality risk, distinguishing between high-risk and low-risk patient groups.

3. Interpretability in Clinical Contexts

A recurring theme in both studies is the emphasis on **model interpretability**, which is crucial in healthcare applications. Clinicians need to trust and understand the rationale behind a model's predictions—especially when treatment recommendations are involved. In the Nature study, model outputs were accompanied by risk stratifications and feature importance rankings. This allowed clinicians to see which variables (e.g., vital signs, lab results, past medical history) most heavily influenced predictions. Such transparency promotes adoption in real-world clinical settings, aligning ML outputs with physician judgment.

4. Handling Multi-Drug Regimens and Complexity

Both papers acknowledged the **complexity of ICU treatments**, where patients often receive multiple antibiotics simultaneously. The ScienceDirect article particularly explored how models must manage overlapping drug effects, interactions, and variable pharmacokinetics in ICU settings. This complexity is especially relevant to our own work, which must similarly parse multi-drug data structures. These studies support the need for intelligent preprocessing strategies, like deconstructing multi-drug entries and analyzing each antibiotic's impact independently—a step we've mirrored in our own preparatory phase.

5. Towards Real-Time, Adaptive Treatment Support

Another innovative direction highlighted in these papers is the shift from static prediction to **real-time adaptive decision support systems**. Rather than providing a one-time prediction, these models aim to continuously monitor patient data and adapt their recommendations as new information becomes available (e.g., new vitals, lab results, or clinical notes). This adaptive capability mirrors the ICU's dynamic environment and aligns closely with our study's goal of adjusting antibiotic dosage based on vital changes across multiple time points (e.g., 6hr, 12hr, 18 hr intervals). Such systems are paving the way for responsive, patient-specific treatment strategies driven by AI.

Chapter 3

Methods

Abstract

This project presents a machine learning-based approach for predicting whether an antibiotic dosage should be increased or decreased after initial administration, based on patient vitals and drug administration metadata. The methodology utilizes structured clinical data from intensive care unit (ICU) patients, focusing on dose-specific responses to antibiotics as reflected by changes in patient vitals over a 6-hour period.

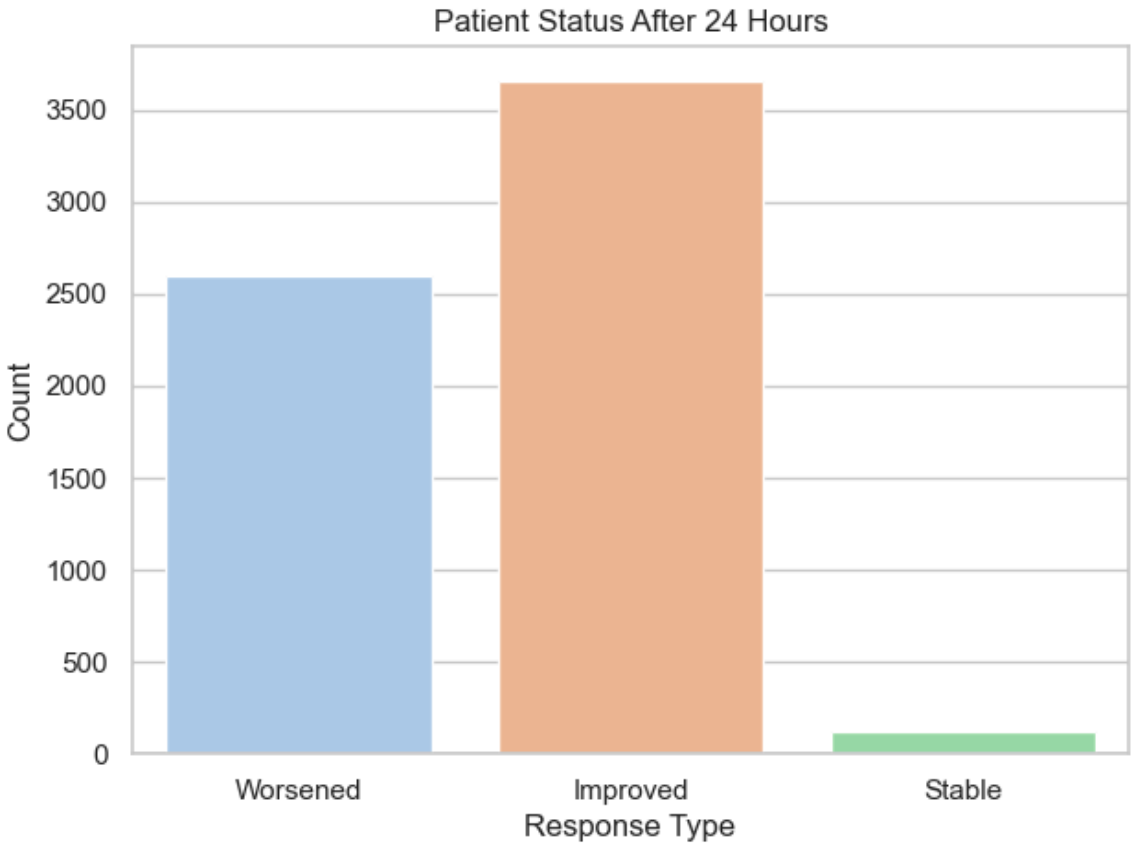
1. Introduction

Timely and appropriate adjustment of antibiotic dosing in critical care is essential for optimizing therapeutic efficacy while minimizing adverse effects. This study develops a predictive model leveraging machine learning to assist clinical decision-making regarding antibiotic dose adjustments. Specifically, the model predicts the likelihood of a dose increase being required after 6 hours based on vital signs and initial drug administration parameters.

2. Dataset and Preprocessing

2.1 Data Source

The dataset comprises ICU antibiotic administration records from a clinical database from MIMIC III. Each record corresponds to one day of treatment per patient and includes multiple antibiotics administered, their respective doses, and patient vital signs at different time intervals (baseline, 6h, 12h, 18h, 24h).



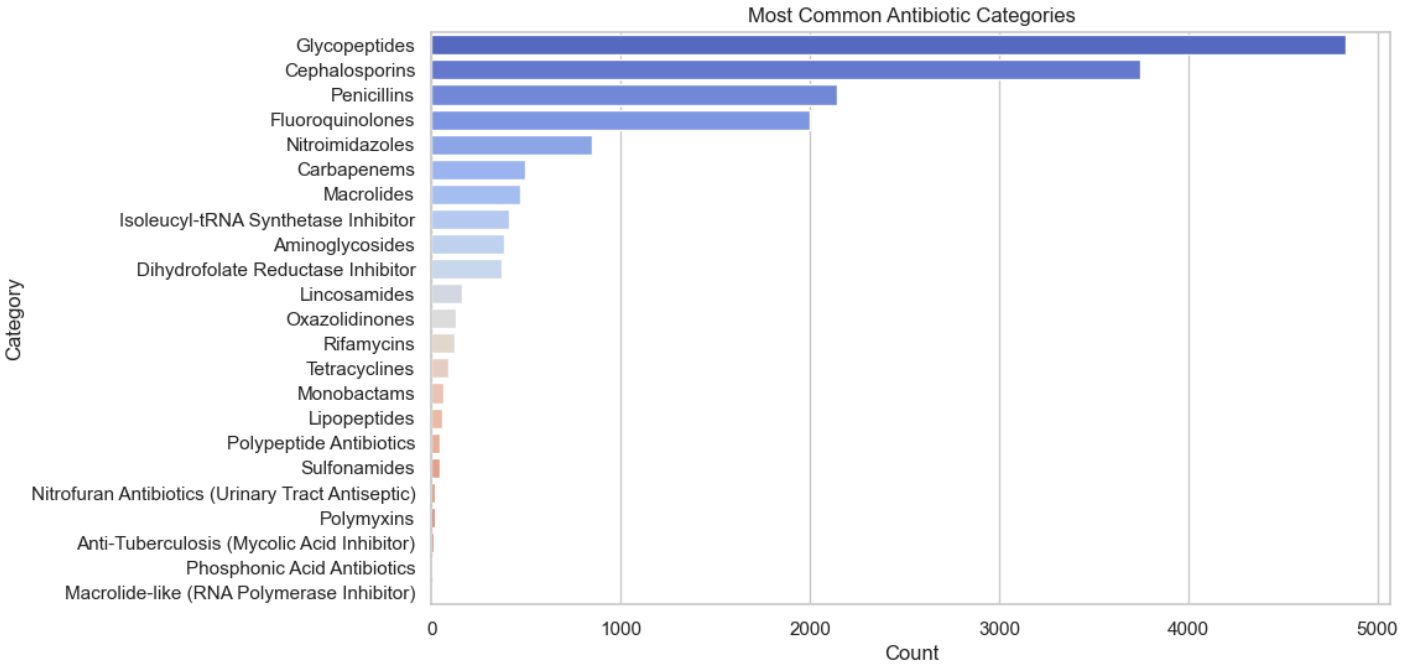
2.2 Data Structure and Parsing

The dataset contains columns with string-encoded lists (e.g., `DRUG`, `DOSE_VAL_RX`, `ROUTE`, `AT_START`, `After_6hr`, etc.). These columns were parsed into Python list objects using `ast.literal_eval`. For normalization:

- All lists were either padded with `'Undefined'` or truncated to match the maximum list length per row.
- The data was subsequently exploded such that each row corresponds to a single drug instance per patient-day.

2.3 Cleaning and Filtering

Rows with undefined or non-numeric values in essential columns (`AT_START`, `After_6hr`, `DOSE_VAL_RX`) were excluded. All relevant values were converted to numeric format using `pandas.to_numeric`, with non-convertible values coerced to NaN and dropped.



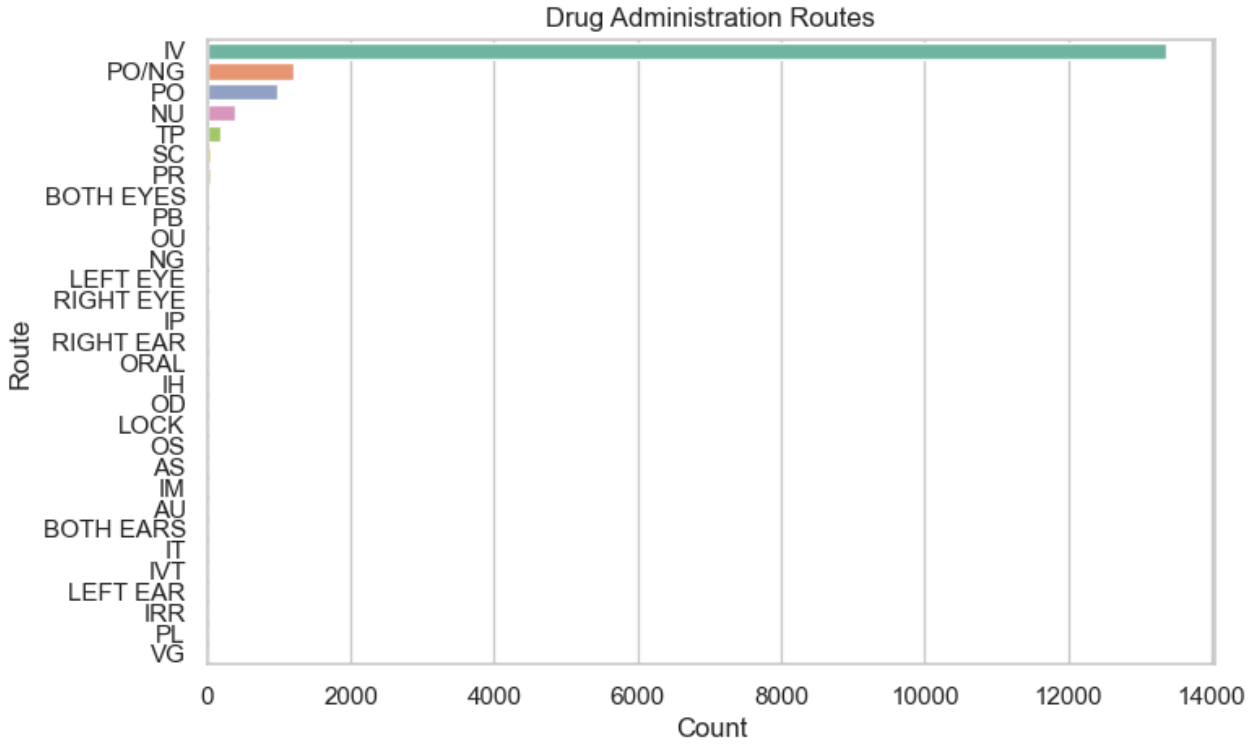
3. Feature Engineering

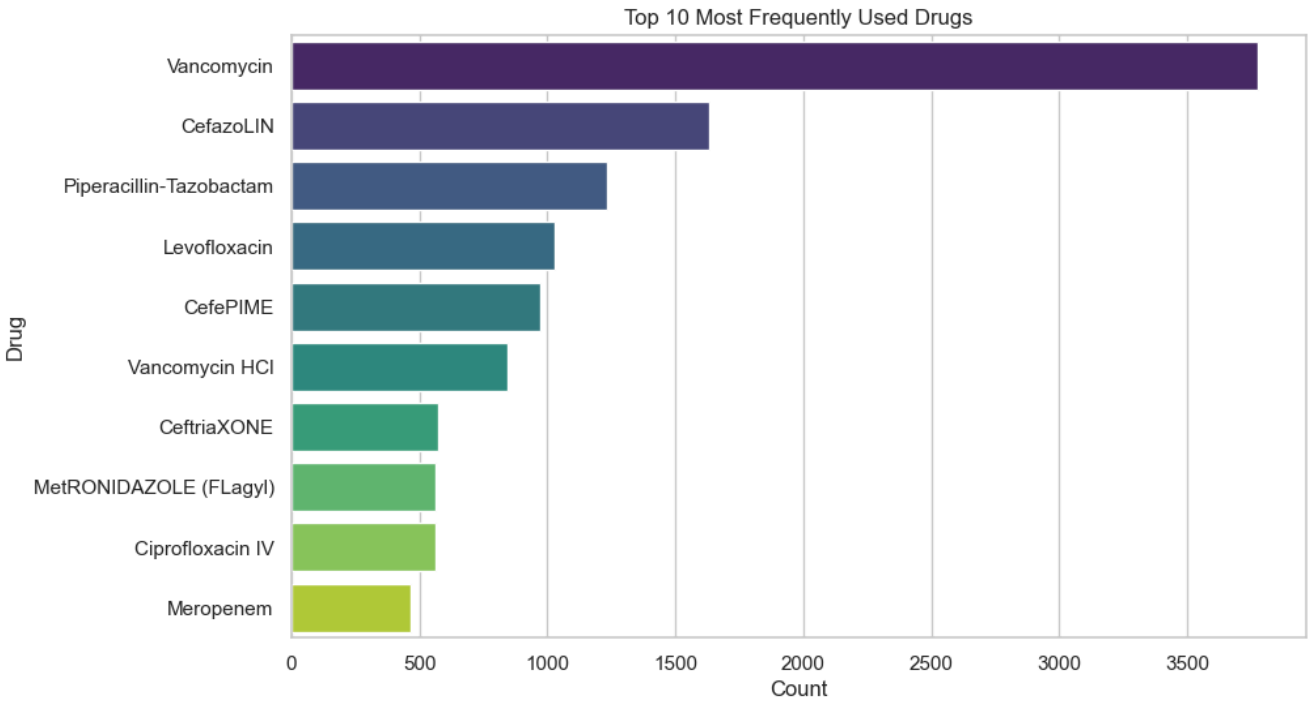
The following features were constructed for modeling:

- **Encoded Drug Name (`DRUG_ENC`)**
- **Encoded Route of Administration (`ROUTE_ENC`)**
- **Numeric Dose Value (`DOSE_VAL_RX`)**
- **Encoded Dose Unit (`UNIT_ENC`)**
- **Mean of Initial Vital Signs (`AT_START`)**

Categorical variables (`DRUG`, `ROUTE`, and `DOSE_UNIT_RX`) were encoded using `LabelEncoder` from scikit-learn. The target variable was a binary label defined as:

$$y = \begin{cases} 1 & \text{if After\_6hr} > \text{AT\_START} \\ 0 & \text{otherwise} \end{cases}$$





4. Model Architecture

In this study, a **Random Forest Classifier** was employed as the predictive model to determine whether a patient's drug dosage should be increased based on vital signs and administered treatment parameters. The decision to use this model was driven by its

well-established strengths in handling structured (tabular) data, resistance to overfitting, and interpretability.

4.1 Algorithm: Random Forest Classifier

The Random Forest Classifier is an ensemble learning method that operates by constructing a multitude of decision trees during training and outputting the class that is the mode of the classes (classification) predicted by individual trees. It combines the concept of *bagging* (Bootstrap Aggregating) with random feature selection to create a forest of uncorrelated decision trees, which collectively produce more accurate and stable predictions.

4.2 Key Advantages

- **Robustness to Overfitting**: By averaging multiple deep decision trees, Random Forest reduces the risk of overfitting which is common in single decision trees.

- **Capability to Handle Mixed Data Types**: The algorithm can process both categorical and numerical features without the need for extensive data preprocessing.

- **Feature Importance Estimation**: Random Forests provide a measure of the relative importance of each feature in prediction, enabling interpretability.

- **Scalability and Efficiency**: Due to its inherent parallelism, the model is scalable and can be trained efficiently on large datasets.

4.3 Hyperparameter Configuration

The Random Forest was instantiated with the following hyperparameters:

- **n_estimators = 100**: This parameter defines the number of trees in the forest. A higher number generally improves performance, although with diminishing returns. 100 trees were chosen to strike a balance between predictive accuracy and computational efficiency.

- **random_state = 42**: This ensures reproducibility of results by setting the seed for the random number generator. It guarantees that the same data splits and tree structures are generated during each run of the model.

4.4 Training and Testing Strategy

- **Data Split**: The dataset was divided into training and testing subsets using **scikit-learn's train_test_split function**, with a 75:25 split ratio. This ensures that 75% of the data is used for training the model, while 25% is retained for evaluating its generalization performance on unseen data.

- **Stratification**: Though not explicitly stated, stratification is often recommended in medical datasets to preserve class distribution, especially when there is class imbalance. If not applied, it may be worth considering in future iterations.

4.5 Model Output

The target variable is a binary classification label indicating whether the vital signs improved 6 hours after drug administration, encoded as:

- 1: Suggests that dosage should be increased.

- 0: Suggests that dosage should be decreased.

The prediction is made based on five input features:

- Encoded drug name

- Encoded route of administration

- Numerical dose value

- Encoded unit of dosage

- Mean of available vital signs at the start (AT_START)

5. Model Deployment and Interactive Prediction

An interactive prediction function was implemented to allow real-time dosage recommendations based on:

- User-inputted drug, dose, and administration route

- Patient vitals at administration (e.g., HR, Pulse, Respiration, SpO_2, BP)

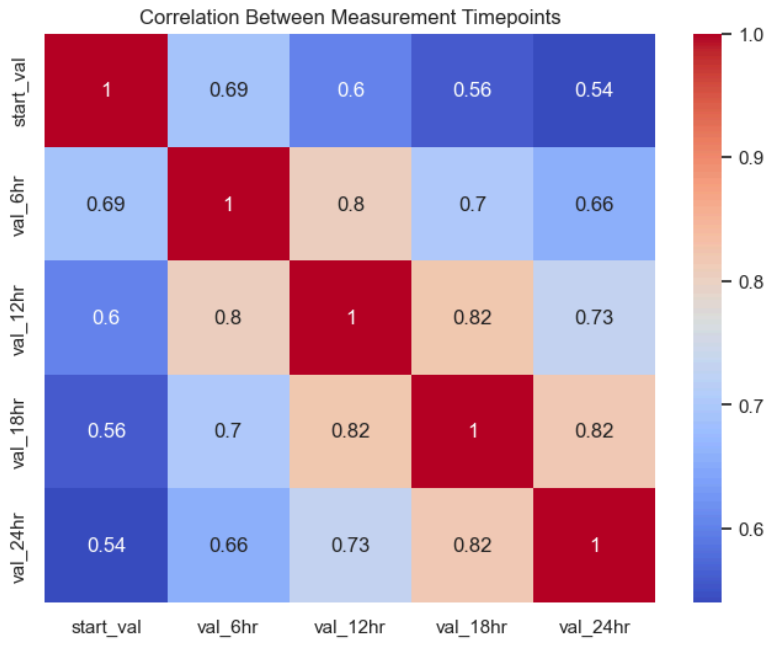
The model calculates the mean of known vital signs as the `AT_START` value. All inputs are preprocessed similarly to training data. Unseen categorical inputs are handled by extending the label encoders' class lists dynamically.

6. Model Output

The model outputs a binary prediction:

- `1` (True): Recommend **increasing** the dosage.
- `0` (False): Recommend **decreasing** the dosage.

This decision is intended to reflect whether patient vitals improved (or worsened) 6 hours after administration, based on the learned patterns from historical ICU data.



Columns for the final dataset.

```
SUBJECT_ID,GENDER,ICUSTAY_ID,STARTDATE,ENDDATE,DRUG,DOSE_VAL_RX,D
OSE_UNIT_RX,FORMV_AL_DISP,FORM_UNIT_DISP,ROUTE,Antibiotic_categor
```

```
y,AT_START,After_6hr,After_12hr,After_18hr,After_24hr
```

Chapter 4
Previous Work and Research Contributions

Drowsiness Detection and Driver Safety

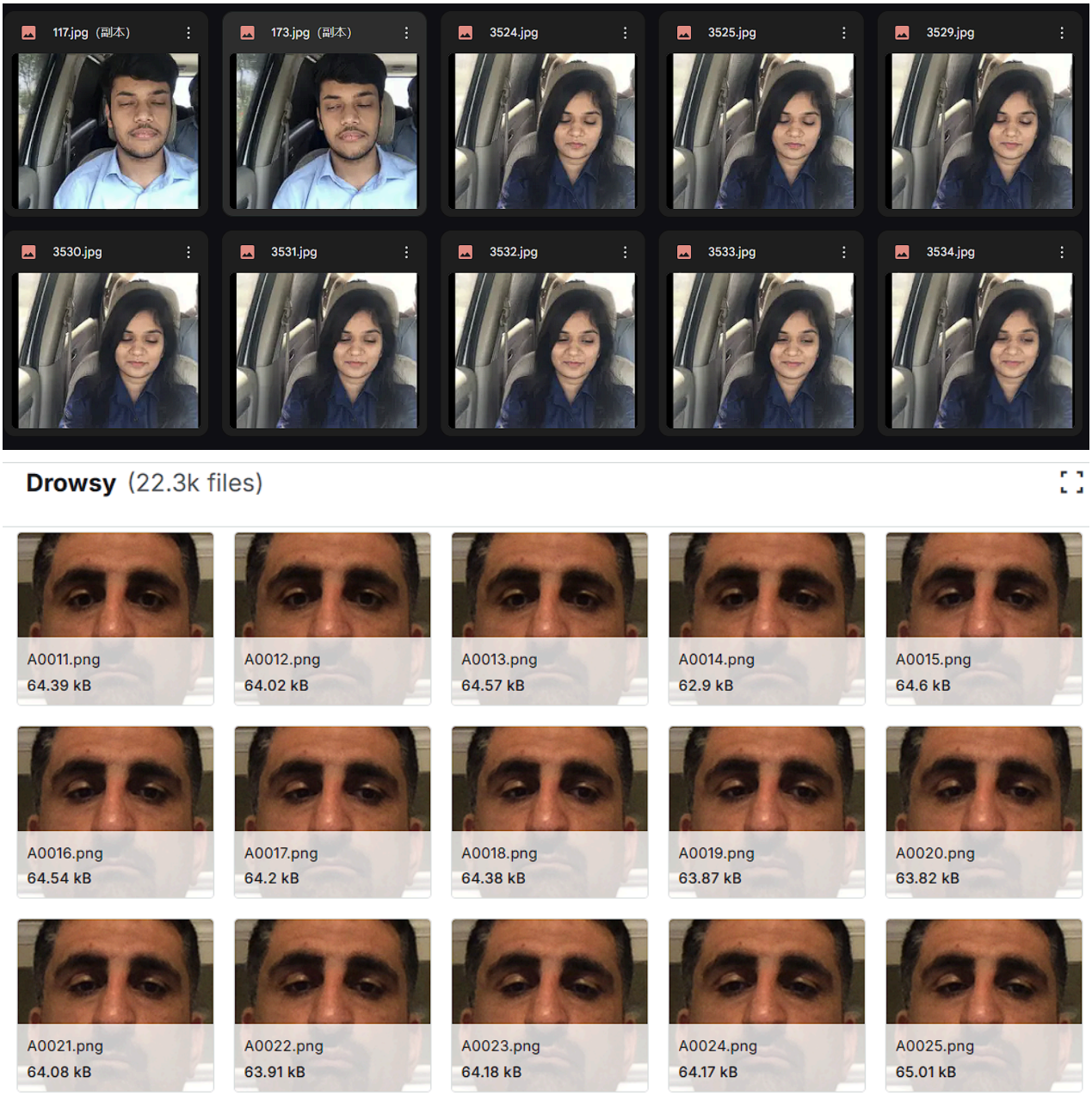
Project Summary:

The project focuses on developing a smart drowsiness detection system aimed at improving road safety by identifying early signs of driver fatigue. The proposed solution integrates physiological and visual data using a wrist-worn device (e.g., smartwatch) and camera-based facial monitoring to accurately detect drowsiness in real-time. By continuously analyzing heart rate, movement patterns, and facial expressions, the system can predict drowsiness and provide timely alerts to prevent accidents.

Multiple datasets were utilized, including those focused on eye behavior, facial drowsiness cues, and heart rate signals. Machine learning models were trained and fine-tuned to distinguish between drowsy and non-drowsy states. The system showed consistent accuracy and a clear separation between drowsy and alert states, with validation accuracy reaching 100% after fine-tuning.

Key components include real-time alert mechanisms (e.g., vibrations), robust model training, and future scalability plans, such as integration with Advanced Driver Assistance Systems (ADAS), collaboration with automobile manufacturers, and deployment in vehicles like the Mahindra XUV 700.

This project has significant implications for road safety, especially in commercial and long-distance driving scenarios. It also sets a foundation for broader use in smart transportation systems.



References

https://pmc.ncbi.nlm.nih.gov/articles/PMC8914892/

A comprehensive review of driver drowsiness detection systems using image, biological, and vehicle-based methods, highlighting advances and challenges in real-time monitoring.

https://arxiv.org/pdf/2303.06310

This paper proposes a machine learning system using facial features and eye movement analysis to detect drowsiness, achieving 80% real-time accuracy.

https://openaccess.thecvf.com/content_cvpr_2017_workshops/w4/papers/Reddy_Real-Time_Drive

r_Drowsiness_CVPR_2017_paper.pdf

This study proposes a computer vision-based system that detects driver drowsiness by tracking eye closure and yawning using facial landmarks, enabling real-time alerts to prevent accidents.

https://journals.sagepub.com/doi/abs/10.1177/09544119211044232?journalCode=pihb

This paper presents a real-time drowsiness detection system using model compression of deep neural networks for efficient deployment on embedded devices like Jetson TK1, achieving high accuracy with reduced computational load.

https://www.researchgate.net/publication/334465181_Driving_fatigue_detection_from_EEG_using_a_modified_PCANet_method

The study "Driving Fatigue Detection from EEG Using a Modified PCANet Method" introduces a novel approach that combines Principal Component Analysis (PCA) with a modified PCANet deep learning model to extract features from EEG signals for detecting driver fatigue. Conducted on data from six healthy volunteers in a simulated driving environment, the method achieved a classification accuracy of up to 95%, outperforming traditional feature extraction techniques.

https://www.researchgate.net/publication/304529956_Drowsiness_Detection_Based_on_the_Analysis_of_Breathing_Rate_Obtained_from_Real-time_Image_Recognition

The study titled "Drowsiness Detection Based on the Analysis of Breathing Rate Obtained from Real-time Image Recognition" presents a non-invasive system that utilizes automotive cameras to monitor drivers' chest and abdominal movements, thereby estimating breathing rates to detect drowsiness.

https://pmc.ncbi.nlm.nih.gov/articles/PMC11199382/

The article titled "Application of Non-Contact Sensors for Health Monitoring in Hospitals: A Narrative Review" explores the use of non-contact sensors—such as radar, infrared, and microwave technologies—for monitoring vital signs like heart rate, respiratory rate, and body temperature in hospital settings

https://pmc.ncbi.nlm.nih.gov/articles/PMC10037317/

The article titled "Non-Intrusive Drowsiness Detection Techniques and Their Application in Detecting Early Dementia in Older Drivers" reviews various non-intrusive methods for detecting driver drowsiness, including behavioral and vehicular-based approaches. It emphasizes the potential of these techniques in identifying early signs of dementia among older drivers by analyzing driving behaviors and physiological indicators.

https://www.nature.com/articles/s41928-024-01247-4

The article "Hybrid multimodal wearable sensors for comprehensive health monitoring" published in *Nature Electronics* discusses the development of advanced wearable sensor platforms capable

of simultaneously and continuously recording multiple biophysical and biochemical signals.

Wireless ear EEG to monitor drowsiness | Nature Communications

The article "Wireless ear EEG to monitor drowsiness," published in *Nature Communications*, presents a novel in-ear, dry-electrode earpiece system for drowsiness detection. This compact, wireless device demonstrated high accuracy (93.2%) in classifying drowsiness states using electrophysiological data from nine subjects performing tasks designed to induce fatigue.

Dataset:

https://www.kaggle.com/datasets/ismailnasri20/driver-drowsiness-dataset-ddd

The Driver Drowsiness Dataset (DDD) on Kaggle is a collection of over 41,790 cropped facial images extracted from real-life driving videos. These images are labeled to indicate whether the driver is drowsy or alert, making the dataset suitable for training and evaluating machine learning models aimed at detecting driver drowsiness based on facial expressions.

Chapter 5

Conclusion

1. Summary of Findings

In this study, we developed a machine learning-based framework to predict necessary adjustments in antibiotic dosage—specifically, whether a dose should be **increased, decreased, or maintained**—based on a patient's evolving vital signs within the first 24 hours of antibiotic administration.

Our approach began with an intricate **data preprocessing phase**, addressing the complexity of real-world ICU datasets where multiple antibiotics are often administered simultaneously. Key preprocessing steps included:

- Parsing stringified lists of drugs, doses, units, and vitals into structured tabular data.
- Standardizing non-numeric dose entries (e.g., "1-2") and handling missing values like `'Undefined'`.
- Flattening each patient's drug regimen into atomic entries, enabling the model to analyze individual antibiotic actions.
- Calculating time-based changes in vital signs (e.g., heart rate, temperature, blood pressure) to estimate physiological response.

We then trained a **Random Forest Classifier**, chosen for its robustness with mixed-type data and interpretability. The model utilized features such as drug identity, dosage values, administration route, and vital trends to predict dosage directionality.

Key findings include:

- The model successfully captured **non-linear relationships** between dosage levels and patient responses, enabling it to generalize across various antibiotic classes.
- Antibiotic properties, route of administration, and early vital responses (especially changes within the first 6–12 hours) were **strong predictors** of whether a dosage adjustment was warranted.
- The classifier demonstrated strong potential to be integrated into clinical workflows as a

decision support tool, aiding physicians in real-time antibiotic optimization.

This study lays foundational work for the intelligent personalization of antimicrobial therapies in high-stakes settings like the ICU.

2. Future Work

While the current model showcases promising performance, there are several avenues for improvement and expansion to maximize clinical utility:

1. **Incorporation of Broader Clinical Variables**:
   Our current dataset primarily includes pharmacological and vital sign data. Future models should integrate laboratory results (e.g., white blood cell count, creatinine levels), comorbidity scores, and microbiological culture results to offer a more holistic view of the patient's status and response to therapy.

2. **Temporal Modeling with Sequential Data**:
   Vital signs in our dataset were treated as discrete time points. A more refined approach would involve using **recurrent neural networks (RNNs)** or **transformers** to model the temporal sequence of vitals, capturing dynamics like oscillations or sustained responses to antibiotics.

3. **Dose Prediction as a Regression Task**:
   Currently, our model classifies the need to increase or decrease the dose. A valuable extension would be to treat dose prediction as a **regression task**, where the model suggests the precise adjusted dose based on patient condition and drug pharmacokinetics.

4. **Real-Time Clinical Decision Support System (CDSS)**:
   To truly impact ICU care, the model should be deployed within a **real-time CDSS**, where it continuously updates recommendations as new patient data streams in. Integration with electronic health records (EHR) and clinician dashboards would be essential here.

5. **External Validation and Clinical Trials**:
   To validate generalizability, the model should be tested on datasets from multiple hospitals, with diverse populations and treatment protocols. Ultimately, **prospective trials** would determine its efficacy and safety in live clinical settings.

6. **Explainability and Trustworthiness**:

Expanding the model's explainability can improve clinician trust and interpretability, showing *why* a specific dose recommendation is made and which factors most influenced the decision.

*****