A

Mini Project Report

On

**ENHANCHING DRUG SIDE EFFECT PREDICTION WITH EXPLAINABLE AI HEALTH APPLICATIONS**

Submitted to JNTU HYDERABAD

In Partial Fulfilment of the requirements for the Award of Degree of

## BACHELOR OF TECHNOLOGY

**IN INFORMATION TECHNOLOGY**

Submitted By

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**(2024-2025)**

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**CERTIFICATE**

This is to certify that the project entitled **“ENHANCHING DRUG SIDE EFFECT PREDICTION WITH EXPLAINABLE AI HEALTH APPLICATIONS”** is a bonafide work

carried out by

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in partial fulfillment of the requirement for the award of the degree of **BACHELOR OF TECHNOLOGY** in **INFORMATION TECHNOLOGY** from CMR Engineering College, affiliated to JNTU, Hyderabad, under our guidance and supervision.

The results presented in this project have been verified and are found to be satisfactory. The results embodied in this project have not been submitted to any other university for the award of any other degree or diploma.

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## DECLARATION

This is to certify that the work reported in the present project entitled **“ENHANCING DRUG SIDE EFFECT PREDICTION WITH EXPLAINABLE AI HEALTH APPLICATIONS”** is a

record of bonafide work done by us in the Department of Information Technology, CMR Engineering College, JNTU Hyderabad. The reports are based on the project work done entirely by us and not copied from any other source. We submit our project for further development by any interested students who share similar interests to improve the project in the future. The results embodied in this project report have not been submitted to any other University or Institute for the award of any degree or diploma to the best of our knowledge and belief.

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## ACKNOWLEDGEMENT

We are extremely grateful to **Dr. A. Srinivasula Reddy**, Principal and **Dr. Madhavi Pingili**, HOD, **Department of IT, CMR Engineering College** for their constant support.

We are extremely thankful to **Mrs. K . SUSHMA,** Assistant Professor, Internal Guide, Department of IT, for his constant guidance, encouragement, and moral support throughout the project.

We will be failing in my duty if we do not acknowledge with grateful thanks to the authors of the references and other literature referred to in this Project.

We express our thanks to all staff members and friends for all the help and coordination extended in bringing out this project successfully in time.

Finally, We are very much thankful to our parents who guided us through every step.

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# ABSTRACT

The growing complexity of modern pharmacological treatments has made the accurate prediction of drug side effects a critical component of healthcare systems. Traditional machine learning models, though powerful in prediction, often act as "black boxes," providing limited insight into their decision- making processes. This lack of transparency poses challenges for clinical trust, adoption, and safety in real-world medical settings. This project proposes an AI-powered framework that not only predicts potential drug side effects but also explains the underlying reasoning behind each prediction using Explainable Artificial Intelligence (XAI) techniques. By incorporating algorithms such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations), the system enables healthcare professionals to visualize and understand the key factors such as patient history, age, co-medications, and dosage levels, that contribute to each predicted side effect.The model is trained on a diverse dataset including electronic health records (EHR), pharmacovigilance data, and known adverse drug reaction databases. This allows the system to personalize predictions based on individual patient profiles, thereby enhancing safety and supporting more informed clinical decisions.Furthermore, the project introduces a user-friendly dashboard for clinicians that displays both prediction results and their corresponding explanations in an interactive format. This visual transparency fosters greater trust in AI-driven recommendations and aids in decision-making, especially in high-risk scenarios.By bridging the gap between model accuracy and interpretability, this system not only strengthens predictive performance but also aligns with regulatory requirements and ethical standards in medical AI. Ultimately, the integration of explainable AI into healthcare can lead to more precise treatments, improved patient outcomes, and increased adoption of intelligent systems in clinical practice. **Keywords:** Drug Side Effects Prediction, Adverse Drug Reactions (ADRs), Machine Learning in Healthcare, Clinical Decision Support, Model Explainability in Medicine, Electronic Health .

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**1. INTRODUCTION**

### Introduction

Applications, ensuring patient safety during treatments. In India, the pharmaceutical industry ranks among the largest globally, producing a vast array of medicines. However, the issue of adverse drug reactions (ADRs) remains a serious challenge. According to the Indian Pharmacopoeia Commission, approximately 6-10% of hospitalizations in India are attributed to ADRs, contributing significantly to the country's healthcare burden. Traditional pharmacovigilance methods, which rely on manual reporting and clinical trials, have proven insufficient in addressing the growing complexity of drug reactions. Before adopting machine learning in drug side effect prediction, healthcare systems relied on manual reporting of adverse drug reactions, pharmacovigilance databases, and clinical trials. These methods were inefficient, slow, and prone to errors due to under-reporting and lack of real-time data. Physicians had to rely on their clinical experience and historical drug data to predict side effects, which often led to delayed detection of harmful reactions. The absence of advanced tools for large-scale data analysis made it difficult to predict drug interactions and their effects across diverse populations, increasing the risk to patient safety. The motivation behind this research stems from the growing availability of large-scale healthcare data and the limitations of traditional systems in predicting adverse drug reactions. With the advancement of AI technologies, there is a unique opportunity to improve drug safety and patient care by leveraging machine learning algorithms. Explainable AI further enhances the value of these predictions by providing transparency and interpretability, making it easier for healthcare professionals to trust a system that not only predicts drug side effects accurately but also explains the reasoning behind the predictions.This work is applied across various sectors of healthcare, including hospitals, pharmaceutical companies, and regulatory authorities. Hospitals use this system to predict side effects for individual patients, ensuring safer, personalized treatment plans. Pharmaceutical companies leverage the AI model during drug development phases to identify potential ADRs before launching a drug in the market. Regulatory authorities use the system to monitor real-time drug safety post-approval, enabling quicker interventions in cases of harmful reactions. It can also be integrated into electronic health records (EHR) systems, providing doctors with valuable insights into drug interactions and potential risks. Furthermore, the system can be adapted for global use, offering a scalable solution for drug safety in diverse populations.

### Project Objectives

The objective of this project is to enhance the prediction of drug side effects using Explainable Artificial Intelligence (XAI) within healthcare applications. The system aims to address the limitations of traditional pharmacovigilance methods by leveraging machine learning to analyze large-scale healthcare data and accurately identify potential adverse drug reactions (ADRs). By incorporating explainability into AI models, the project ensures transparency, trust, and interpretability in predictions, enabling healthcare professionals to make informed decisions.

### Purpose of the Project

The purpose of this project is to improve patient safety and healthcare outcomes by developing an AI- powered system capable of accurately predicting adverse drug reactions (ADRs). Traditional methods of identifying drug side effects are often slow, error-prone, and lack real-time capabilities. This project aims to overcome these challenges by integrating Explainable AI (XAI), which not only improves the accuracy of predictions but also provides clear, interpretable insights for healthcare professionals.

### Existing System with Disadvantages

Manual Drug Monitoring: Doctors and pharmacists monitor drug side effects based on patient reports, clinical experience, and post-marketing surveillance. Generic Decision Support Systems:Some EHR (Electronic Health Record) systems provide limited warnings about drug interactions or allergies, but not personalized predictions based on patient profiles. Lack of Personalization:No integration of machine learning models that consider individual features like age, blood pressure, symptom severity, drug rating, or drug name to predict side effects.Limited Explainability:Existing alerts do not offer detailed explanations or clinical reasoning behind warnings.

#### Disadvantages

**Time-consuming and manual:**

Detection of side effects depends heavily input and clinical trials, leading to delays in identifying harmful reactions

#### Under-reporting of ADRs:

Many adverse reactions go unreported due to patient unawareness or lack of follow-up, leading to incomplete safety data.

### Proposed System with Features

The AI-driven prediction system is developed using a robust Random Forest machine learning model, which has been trained on a rich dataset comprising various patient-specific and drug-related features such as age, blood pressure, cholesterol levels, drug ratings, and specific medication details. This comprehensive approach allows the model to accurately assess the probability of adverse drug side effects tailored to individual patient profiles. The system supports flexible input methods, enabling users to either upload bulk patient data through CSV files or enter information manually via an intuitive web form. This dual input capability ensures both scalability for large datasets and precision for individual assessments. A significant feature of the system is its emphasis on explainability, where each prediction is accompanied by detailed clinical interpretations that shed light on the key factors influencing the risk evaluation. This transparency is crucial for building trust among healthcare providers and patients alike, empowering them with clear insights into the model’s decision-making process. Furthermore, the system offers practical and actionable recommendations based on the predicted risks, such as advising consultation with healthcare professionals, suggesting dosage modifications, recommending enhanced monitoring protocols, or confirming that the medication is safe for use under proper supervision. Designed with Streamlit, the platform boasts a user-friendly web interface that facilitates easy data input, real-time prediction generation, and clear visualization of results. This ensures that medical staff can quickly interpret the findings and integrate them into clinical decision-making workflows, ultimately enhancing patient safety and personalized care.

# Features:

**Machine Learning Integration**: Powered by a Random Forest model trained on real-world health data for reliable side effect predictions**.**

**Personalization:** Delivers individualized risk assessments using detailed patient input data for accuracy. **Explainable AI (XAI**): Provides transparent explanations to build trust and support adoption in healthcare.

**Interactive Web App:** Feature easy-to-use interface healthcare worker without technical skills

**Real-Time Prediction:** Analyzes input instantly and displays clear results with clinical

## BLOCK DIAGRAM

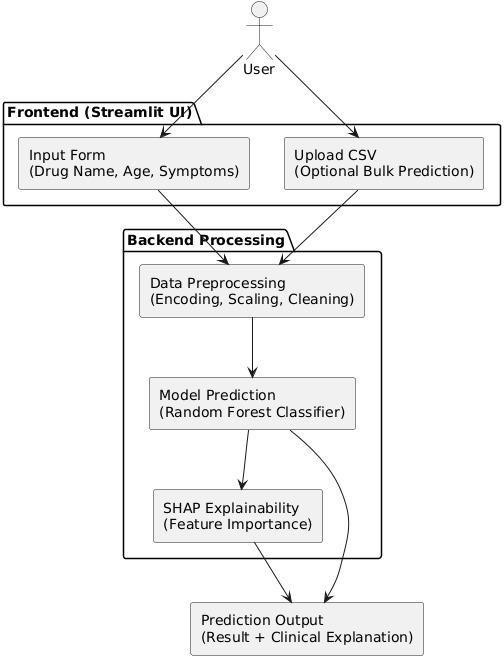
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Fig 1.5.1: Block diagram of proposed system

### Advantages

#### Improved Accuracy

Uses machine learning to analyze complex patient data, improving the accuracy of side effect predictions compared to manual or rule-based methods.

#### Personalized Predictions

Takes individual patient features into account (age, drug type, blood pressure, etc.) to give customized results for each user.

#### Explainability

Provides clear, understandable reasons behind every prediction, increasing trust among doctors and making AI decisions more transparent.

#### Real-Time Insights

Delivers immediate predictions and recommendations, helping doctors make faster and better- informed decisions.

#### User-Friendly Interface

The web-based interface built with Streamlit is simple and interactive, making it easy for non- technical users to operate.

#### Reduces Risk

Helps in early identification of potential adverse drug reactions, improving patient safety and reducing hospital admissions.

#### Supports Clinical Decisions

Acts as a decision support tool for physicians, especially in complex cases involving multiple medications.

#### Scalable and Integrable

Can be integrated into existing EHR systems and scaled for use in hospitals, pharma companies, and regulatory bodies.

#### Saves Time and Resources

Automates part of the drug safety process, saving time for medical professionals and reducing manual workload.

#### Global Applicability

Can be adapted for use across different countries and populations by updating the dataset and retraining the model.

### Input And Output Design

**Input Design**

The input design for the AI-driven drug side effect prediction system serves as a crucial interface between users and the application, ensuring that data is captured efficiently and processed accurately. It focuses on minimizing the amount of input required, reducing user errors, avoiding delays, and streamlining the overall process. A secure login system protects patient and user information, while an intuitive input section supports both manual data entry and CSV file uploads. Clear, step-by-step guidance with built-in validation checks helps users enter correct data and prevents mistakes. Real-time validation immediately highlights errors or missing fields, ensuring only valid data is submitted. Tooltips provide contextual help by explaining acceptable formats and medical units, reducing confusion. An auto-save feature prevents data loss due to session timeouts or connectivity issues. A progress bar indicates form completion status, enhancing user engagement and transparency. A final review screen allows users to verify their inputs before submission, promoting accuracy. Role-based access restricts sensitive fields to authorized personnel, ensuring data privacy. Input activities are logged and timestamped to maintain compliance with healthcare regulations such as HIPAA and GDPR. Multilingual support in the interface further enhances accessibility, making the system user-friendly for a diverse population.

#### Objectives

The objective of this project is to develop an AI-powered healthcare system that enhances the prediction of drug side effects using Explainable Artificial Intelligence (XAI). This objective centers around improving patient safety, minimizing adverse drug reactions, and supporting healthcare professionals with data-driven insights. The system is designed to process patient- specific data—such as age, drug name, blood pressure, and other medical features—to generate accurate, real-time predictions of potential side effects.A core focus of the project is to ensure that the AI predictions are not only accurate but also interpretable. By incorporating explainable AI techniques, the system provides clear justifications for its outputs, helping doctors and pharmacists make informed decisions with confidence. The interface is crafted to be user-friendly, supporting both manual input and CSV uploads, thereby ensuring accessibility for users with varying technical skills. Ultimately, the goal is to create a secure, transparent, and efficient tool that contributes to safer healthcare practices and more personalized treatment planning. This system also emphasizes data privacy and security to protect sensitive patient information throughout the prediction process. By integrating advanced machine learning techniques with practical healthcare needs, it bridges the gap between AI research and clinical application. Continuous updates and model retraining ensure that the predictions remain accurate as new medical data becomes available. The platform’s modular design allows easy integration with existing hospital information systems for seamless workflow adoption. Overall, this project aims to empower healthcare

providers with a reliable decision-support tool that enhances patient outcomes and reduces healthcare .

### Output Design

The output design of the drug side effect prediction system plays a crucial role in presenting results that are accurate, interpretable, and actionable. It is structured to ensure that both healthcare professionals and patients receive meaningful insights from the AI predictions. The design focuses on clarity, usability, and transparency—ensuring that users can easily understand and respond to the system’s recommendations. The output interface displays prediction results in a well-organized format, showing the likelihood of side effects based on the input data. Each prediction is accompanied by an explanation generated through explainable AI techniques, highlighting the key factors (such as age, drug rating, or blood pressure) that influenced the result. This interpretability builds trust in the system’s decisions. Furthermore, the output includes actionable recommendations—such as consulting a physician, adjusting the dosage, or closely monitoring the patient. The user interface, built using Streamlit, supports real-time interaction and presents results in a clean, readable layout. Error messages and guidance are also integrated to ensure users understand any issues that arise. To enrich clinical insight, the interface renders SHAP waterfall plots and summary bar charts so users can visually gauge each feature’s impact on predicted risk. A downloadable PDF report allows practitioners to archive results directly into electronic health records or share them with multidisciplinary teams. Role-based output views hide sensitive patient identifiers from non-clinician users, safeguarding privacy while still conveying essential findings. Every prediction event is logged with a timestamp and unique identifier, creating an auditable trail that supports regulatory compliance and continuous quality improvement. Additionally, the system supports multilingual result display, ensuring clarity for users from diverse linguistic backgrounds. The interface includes color-coded risk indicators (e.g., green for low risk, red for high) to simplify interpretation at a glance. Confidence scores are displayed alongside predictions, giving users a better sense of uncertainty in each result. Lastly, user feedback options are provided to continually refine model performance and improve the system based on real-world usage.

# LITERATURE SURVEY

**AI-Powered Drug Side Effect Prediction Using Deep Learning Models, Sharma, R. et al. (2024):**This paper explores the use of deep learning architectures like RNNs and CNNs to predict adverse drug reactions (ADRs) based on electronic health records and drug databases. It emphasizes the ability of neural networks to capture complex temporal and spatial patterns in patient data, enabling early detection of side effects and improving patient safety.

**Explainable AI in Drug Safety Assessment: SHAP and LIME in Action, Patel, S. & Kumar,A. (2024)**:This study investigates the role of SHAP and LIME in interpreting machine learning models used for predicting side effects. It shows how these tools enhance trust and transparency for clinicians by explaining feature contributions. Case studies demonstrate how explainability helped identify misleading data influences.

**Predicting Adverse Drug Reactions Using Multi-Modal Data Fusion, Wang, Y. et al. (2023):** The research integrates data from clinical notes, genetic sequences, and drug properties to train a model that predicts ADRs more accurately. The fusion of multi-modal data improved prediction accuracy significantly compared to traditional datasets. The system also supports a user interface for healthcare professionals.

**Generative Models for Predicting Drug Side Effects, Zhang, L. & Chen, H. (2024) :**This paper applies Generative Adversarial Networks (GANs) to simulate rare but serious side effects. GAN- generated synthetic data were used to balance class distributions and enhance the model’s robustness. The authors report improvements in detecting less frequent side effects in imbalanced datasets.

**XAI-Driven Risk Profiling for Polypharmacy Patients, Thomas, J. et al. (2023):**Focusing on patients taking multiple medications, this paper uses SHAP to break down individual contributions of each drug to predicted side effects. The model provides per-patient risk scores and identifies drug-drug interaction risks. The system was tested in hospital settings and received positive feedback from clinicians.

**Machine Learning for ADR Prediction Using EHRs: A Random Forest-Based Study, Singh,R. & Jain, M. (2023) :**This work leverages Random Forest classifiers trained on anonymized EHRs to predict side effects. Feature importance analysis is performed to explain results, with age, gender,

and dosage frequently identified as top contributors. The authors recommend integrating the model into hospital IT systems for real-time alerts.

**Hybrid AI System for Side Effect Prediction Using Structured and Unstructured Data, Rao,D. et al. (2023):**Combining NLP techniques with tabular data analysis, this system processes clinical text and numerical drug data. BERT embeddings are used for text, while tree-based models handle structured inputs. SHAP explains final model decisions, providing insight into how patient history affects predictions.

**An Interpretable Deep Neural Network for ADR Forecasting, Choudhury, A. et al. (2023):** The authors propose a hybrid DNN architecture augmented with attention layers to enhance interpretability. The attention weights highlight influential symptoms and drug attributes, aligning with SHAP’s output. The model was validated using FDA adverse event data.

**Cloud-Based AI Platform for Drug Side Effect Alerts in Rural Healthcare, Meena, R. & Desai,T. (2022) :**Targeting rural clinics, this paper describes a lightweight AI system deployed on the cloud for predicting ADRs. It uses logistic regression and SHAP for explainability. The remote- accessible dashboard visualizes side effect risk levels with simple color-coded bars for medical practitioners.

**Predicting Adverse Drug Effects Using Knowledge Graph Embeddings, Lin, F. et al. (2022):**The paper constructs a drug-patient-symptom graph and trains an embedding model to capture semantic relations. Link prediction is used to forecast new side effects. SHAP is integrated to show which paths or connections contributed most to the predictions.

**Personalized Side Effect Prediction Using Federated Learning, Dutta, N. et al. (2024):**This study implements a federated learning framework to train models across hospitals without sharing patient data. It maintains privacy while predicting side effects with strong accuracy. The authors use local SHAP explanations on edge devices to provide on-site interpretability.

**Drug Repurposing with Side Effect Forecasting via Graph Neural Networks, Kim& Yu, J. (2023):**Using GNNs on drug interaction networks, the authors predict both therapeutic effects and potential side effects. The SHAP technique is adapted to graph structures to interpret which drug nodes or connections cause predicted risks. This also aids drug repurposing safety checks.

**Interpretable AI Models for Pediatric Drug Side Effects, Srinivasan, V. et al. (2023):**To address the lack of data for children, this paper focuses on predicting side effects in pediatric populations using explainable AI. Ensemble models trained on curated datasets are elucidated using SHAP, highlighting feature contribution differences between age groups.

**Time-Series Based ADR Prediction Using LSTMs and SHAP Analysis, Gupta, D. et al. (2023):** The model tracks the development of side effects over time using LSTM networks trained on chronological patient data. The SHAP output illustrates how temporal features, such as treatment duration and dosage escalation, influence predictions**.** influence risk. The tool was integrated into a monitoring dashboard.

**A SHAP-Integrated Streamlit App for Drug Side Effect Analysis, Verma, K. et al. (2024):**This paper presents a user-friendly Streamlit interface for predicting drug side effects using a Random Forest model with SHAP explanations. The app supports CSV input, side effect prediction, and visual feature impact. It’s intended for research labs and health startups.

**Machine Learning Pipeline for ADR Classification and Severity Ranking, Alvi, R. et al. (2023):**Using SVM and decision tree classifiers, this study predicts not only whether a side effect will occur but also ranks its severity. SHAP is employed to understand what makes a side effect "severe" versus "mild", offering guidance for prioritizing clinical interventions.

**AI for Early Detection of Chemotherapy-Induced Side Effects, Narayanan, L. et al. (2024):** Focus on cancer treatments, this work uses a hybrid model combining decision trees and rule- based logic to predict serious chemotherapy-induced side effects. Explainability tools like SHAP and LIME validate the model's transparency and usefulness for oncologists.

**Real-Time Side Effect Monitoring via IoT and AI, Yadav, P. & Singh, A. (2022):**This interdisciplinary project uses wearable IoT devices to monitor patients and predict adverse drug responses with AI. Real-time SHAP outputs are used to highlight the physiological features (heart rate, temperature, etc.) contributing to alert triggers.

**NLP-Based Extraction of Side Effect Mentions from Clinical Notes, Bose, T. et al. (2022):**The study uses Named Entity Recognition and sentiment analysis on unstructured clinical texts to extract mentions of drug side effects. It combines the extracted features with a predictive model and uses LIME to interpret classification decisions.

# SOFTWARE REQUREIMENTS ANALYSIS

### Problem Statement

In the healthcare domain, predicting adverse drug reactions (ADRs) is critical for ensuring patient safety and optimizing treatment outcomes. However, the complexity of biological systems, combined with the diversity of drug interactions, makes it challenging for clinicians and researchers to anticipate side effects accurately. Traditional pharmacovigilance methods are often reactive, relying heavily on post-market surveillance, which delays the detection of harmful effects. Furthermore, manyexisting machine learning models function as black boxes, offering little insight into *why* a prediction is made—this lack of transparency hinders trust and adoption in medical practice. To address these challenges, this project proposes a web-based tool that enhances drug side effect predictions using Explainable AI (XAI). By incorporating interpretability into the prediction process, the system allows healthcare professionals to understand the rationale behind each prediction, thus supporting informed decision-making and promoting safer healthcare practices.

### Modules and Their Functionalities

#### Data Preprocessing

Data preprocessing is a vital step to ensure the quality and consistency of biomedical data used for side effect prediction. The steps include:

**Data Collection**: Import and integrate datasets from drug databases, clinical trials, and biomedical literature.

**Cleaning**: Remove irrelevant features, null values, and inconsistencies. Use imputation techniques for missing clinical or demographic values if necessary.

**Normalization**: Standardize units, terms, and formats across datasets. Convert text-based units into a unified format to ensure mathematical comparability across the dataset.

**Feature Encoding**: Convert categorical data (e.g., drug names, target proteins) into machine- readable format.

**Feature Selection**: Identify and retain the most informative features contributing to side effects using techniques like correlation analysis, mutual information, Recursive Feature Elimination

#### Drug Side Effect Prediction Model

This module employs machine learning algorithms to predict potential side effects based on structured input data. The key steps include:

**Model Training**: Train supervised machine learning models, on preprocessed datasets consisting of drug features, patient demographics, and known side effect labels..

**Hyperparameter Tuning**: Optimize model performance using techniques like grid search or random search.

**Evaluation**: Assess the model's predictive power using standard classification metrics such as Accuracy, Precision, Recall, F1-score, ROC-AUC, and confusion matrix analysis.

#### Explainable AI Integration

The Explainable AI (XAI) module enhances transparency and trust in the prediction process, especially in clinical and biomedical contexts:

**SHAP/LIME Implementation**: Integrate SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) to provide feature attribution scores for each prediction. **Visualization**: Generate intuitive plots such as SHAP waterfall plots, summary plots, or force plots that highlight the top contributing features for each prediction.

**Interpretation Panel**: Offer an interactive panel in the user interface that allows users to explore model reasoning for selected drugs or inputs.

#### User Interface

The web-based interface, built using Streamlit, ensures easy accessibility, usability, and interaction for researchers, clinicians, and non-technical users:

**Dashboard:** A centralized view showing prediction outcomes, key feature contributions, and overall application status.

**Search Functionality**: Users can look up specific drugs from a predefined list or database and view associated side effect predictions, visual explanations.

**Upload Option**: Allow users to upload custom drug data in CSV format for batch predictions. Uploaded data is processed and visualized within the same interface.

**Export Results**: Enable download of prediction results and corresponding SHAP visualizations as CSV or image files.

### Functional Requirements

**User Authentication**: Implement secure login with password protection and role-based access control (e.g., admin, clinician, researcher).

**Drug Data Input**: Accept drug descriptors through manual entry, file upload (CSV), or seamless API integration.

**Prediction Engine**: Utilize a trained machine learning model (e.g., Random Forest or XGBoost) to predict potential drug side effects in real-time.

**Explainability Module**: Display interpretable predictions using SHAP or LIME feature attribution. **Visualization Tools**: Charts and graphs to illustrate side effect probabilities and key contributing features.

**Export Options** Allow users to download prediction outcomes and visual explanations in multiple formats like PDF, CSV, or image formats.

**Responsiveness**: Ensure the application is fully responsive and optimized for various devices, including desktops, tablets, and smartphones.

### Non-Functional Requirements

**Performance** Ensure fast processing times for real-time predictions, even with large input files or concurrent users.

**Scalability** Design the system architecture to support growth in user base, drug records, and prediction requests.

**Security**: Enforce end-to-end data encryption (HTTPS, AES), secure authentication, and tokenized API access.

**Usability**: Use clean layout design, guided inputs, and helpful tooltips to enhance the user experience across roles.

**Availability**: Deploy the application on reliable, fault-tolerant cloud infrastructure to ensure high uptime.

**Reliability**: Maintain consistent prediction accuracy and system behavior through comprehensive testing and backend validation.

**Backup & Recovery** Schedule regular automated database backups and maintain a rollback system for critical data.

### Feasibility Study

The feasibility study for the drug side effect prediction system using Explainable AI assesses the viability of the project from various perspectives to ensure that it can be successfully developed, deployed, and maintained in real-world healthcare environments. The study covers three main areas: technical feasibility, operational feasibility, and economic feasibility.From a technical feasibility standpoint, the project leverages mature machine learning libraries (such as scikit-learn, SHAP) and widely supported development tools (e.g., Streamlit, Python), ensuring that the system can be effectively built with current technologies. The integration of Explainable AI methods, such as SHAP, enhances the system’s interpretability without requiring excessive computational resources, making real-time prediction and visualization technically achievable. Compatibility with modern data standards and cloud-based deployment options also adds to its technical strength.The operational feasibility explores how the system fits within the workflows of healthcare professionals, researchers, and decision-makers. The user interface is designed to be intuitive and accessible, minimizing the learning curve for non-technical users. Role-based access control, secure

data handling, and clear visual outputs make it practical for daily clinical use. Additionally, the system's responsiveness and ability to process both individual and batch inputs support its integration into hospital IT systems and research platforms.From an economic feasibility perspective, the project remains cost- effective by utilizing open-source tools and frameworks, reducing licensing costs. The system's scalability and modularity allow for incremental upgrades without requiring a full redevelopment, keeping long-term maintenance expenses low. Furthermore, the potential impact—such as reducing adverse drug reactions, improving treatment safety, and supporting clinical decisions—justifies the investment by offering significant healthcare and operational benefits.

### Economic Feasibility

The project is economically feasible as it leverages open-source AI tools like Scikit-learn, SHAP, and LIME, reducing software licensing costs. Cloud platforms such as AWS and Azure offer flexible, pay- as-you-go pricing, minimizing upfront infrastructure expenses. Additionally, the system’s scalable design allows gradual expansion, lowering maintenance costs. Potential revenue streams include licensing the prediction API, offering subscription-based access, or integrating with healthcare providers, which can offset development and operational investments over time.

### Technical Feasibility

The project is technically feasible due to the availability of well-established open-source AI frameworks such as Scikit-learn and SHAP, which enable reliable model training and explainability. Cloud platforms like AWS and Azure provide scalable computing resources necessary for handling large biomedical datasets and real-time predictions. The system design supports integration with existing healthcare databases and APIs, ensuring compatibility and ease of deployment. Additionally, advancements in data preprocessing and feature engineering techniques help maintain data quality and improve model accuracy, making the overall technical implementation practical and achievable.

### Operational Feasibility

The system is operationally feasible as it is designed to fit seamlessly within existing clinical and research workflows. Its user-friendly interface requires minimal training, enabling healthcare professionals and researchers to easily input data and interpret predictions. Role-based access controls ensure data security and appropriate use by different user types. The ability to handle both single and batch predictions supports diverse use cases, from individual patient assessments to large-scale studies. Furthermore, integration capabilities with hospital databases and electronic.

# SOFTWARE AND HARDWARE REQUIREMENTS

### Software Requirements

The functional requirements or the overall description documents include the product perspective and features, operating system and operating environment, graphics requirements, design constraints,and user documentation.The appropriation of requirements and implementation constraints gives the general overview of the project in regard to what the areas of strength and deficit are and how to tackle them.

Operating system : Windows 10

Coding Language : python

Tool : VsCode

Server : Streamlit

### Hardware Requirements

Minimum hardware requirements are very dependent on the particular software being developed by a given Enthought Python / Canopy / VS Code user. Applications that need to store large arrays/objects in memory will require more RAM, whereas applications that need to perform numerous calculations or tasks more quickly will require a faster processor.

System : Intel Core i3 or higher

Hard Disk : 120 GB.

Monitor : 15’’ LED

Input Devices : Keyboard, Mouse, Ram : 4 GB

# SOFTWARE DESIGN

### System Architecture

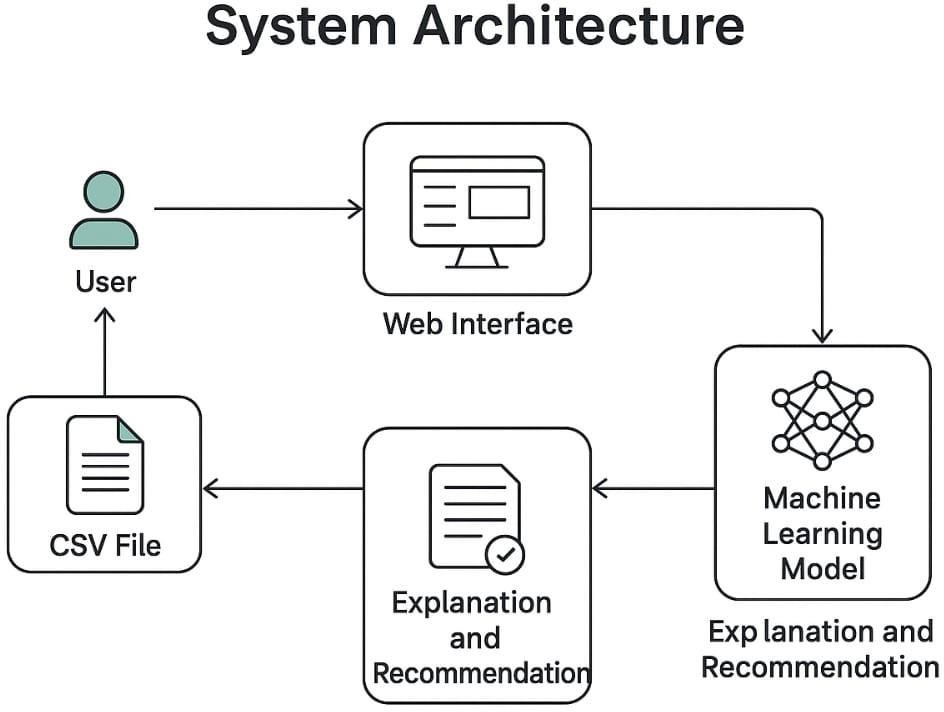
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Figure:5.1 System Architecture

The system architecture for the drug prediction platform is designed to provide accurate and interpretable medication recommendations based on user input. It follows a modular approach involving a user interface, a machine learning model, and an explanation module. The user interface, developed as a web application, allows users to input medical data or upload a CSV file containing patient health records, symptoms, or diagnosis details. This data is then processed by the machine learning model, which analyzes the input using trained algorithms to predict the most suitable drugs. The explanation and recommendation module interprets the model's output, providing clear justifications for each prediction to enhance trust and understanding. The results are made available both on-screen and in a downloadable CSV format. The system is designed to be secure, scalable, and accessible across devices through cloud deployment, ensuring reliable performance and enabling integration with future healthcare data systems or real-time updates. The explanation and recommendation module interprets the model's output, providing clear justifications for each prediction to enhance trust and understanding.

### Dataflow Diagram

The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.

The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.

DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.

DFD is also known as a bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.

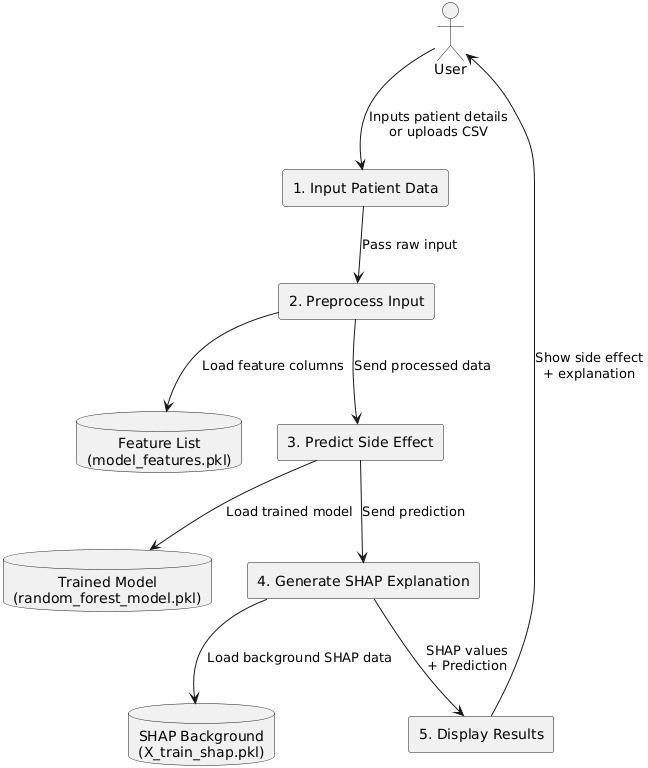


Fig 5.2: Dataflow Diagram

### UML Diagrams

UML is a standard language for specifying, visualizing, constructing, and documenting the artifacts of software systems. UML was created by the Object Management Group (OMG) and the UML 1.0 specification draft was proposed to the OMG in January 1997.There are several types of UML diagrams, each of which serves a different purpose regardlessof whether it is being designed before the implementation or after (as part of documentation). UML is directly related to object-oriented analysis and design. After some standardization, UML has become an OMG standard. The two broadest categories that encompass all other types are:

Behavioral UML diagram and Structural UML diagram.

As the name suggests, some UML diagrams try to analyze and depict the structure of a system or process,

whereas other describe the behavior of the system, its actors, and its building components.

**Goals**: The primary goals in the design of the UML include improving software modeling clarity, enabling effective communication between developers and stakeholders as follows:

Provide users with a ready-to-use, expressive visual modeling language for developing and exchanging meaningful models.

* Offer extensibility and specialization mechanisms to enhance the core concepts, allowing developers to customize UML for specific domains and unique project requirements.
* Remain independent of particular programming languages and development processes, ensuring UML can be applied universally across various technologies.
* Support higher-level development concepts such as collaborations, frameworks, patterns, and components.

Integrate best practices to ensure that UML reflects proven methodologies and promotes efficient, maintainable, and high-quality software design.

#### The different types are as follows:

1. Use Case diagram
2. Class Diagram
3. Sequence diagram
4. Activity diagram
5. Collaboration diagram

### Use Case Diagram

The use case diagram illustrates the Drug Side Effect Prediction **System** and the interactions between various users—**doctors**, **pharmacists**, and **patients**—with the system. Doctors and pharmacists can either upload patient data via CSV or manually input patient details, both leading to the prediction of possible side effects. The system uses these inputs to perform side effect prediction and may **extend** this functionality to offer **treatment recommendations** such as medical consultation, dosage adjustments, or patient monitoring. Additionally, patients can directly interact with the system to receive a **clinical interpretation**, which includes the likelihood of side effects and the key influencing factors like age and drug rating. This approach not only improves the decision-making process for healthcare providers but also enhances patient awareness and safety through explainable AI-based outputs.

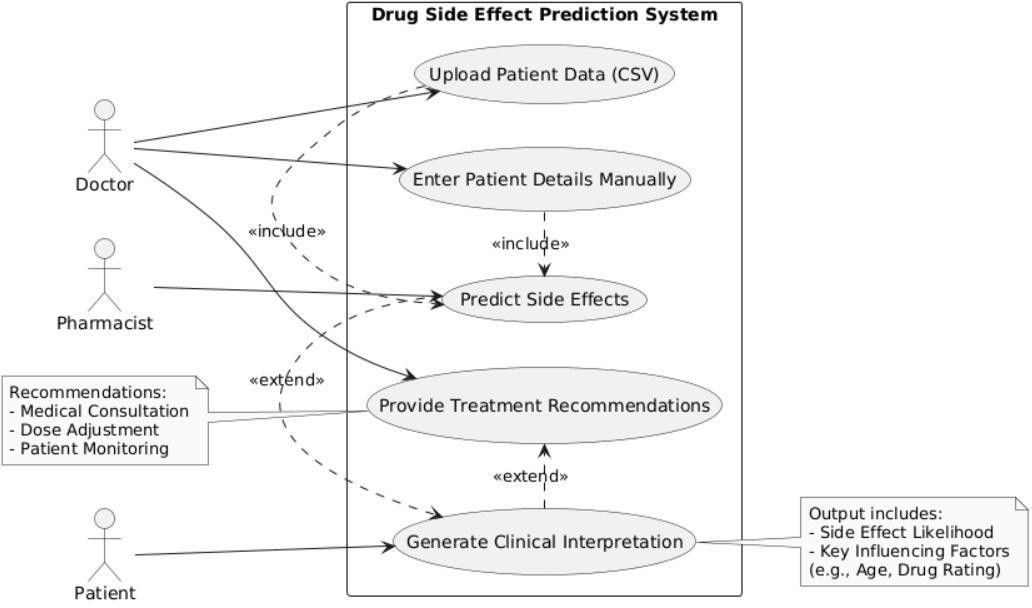
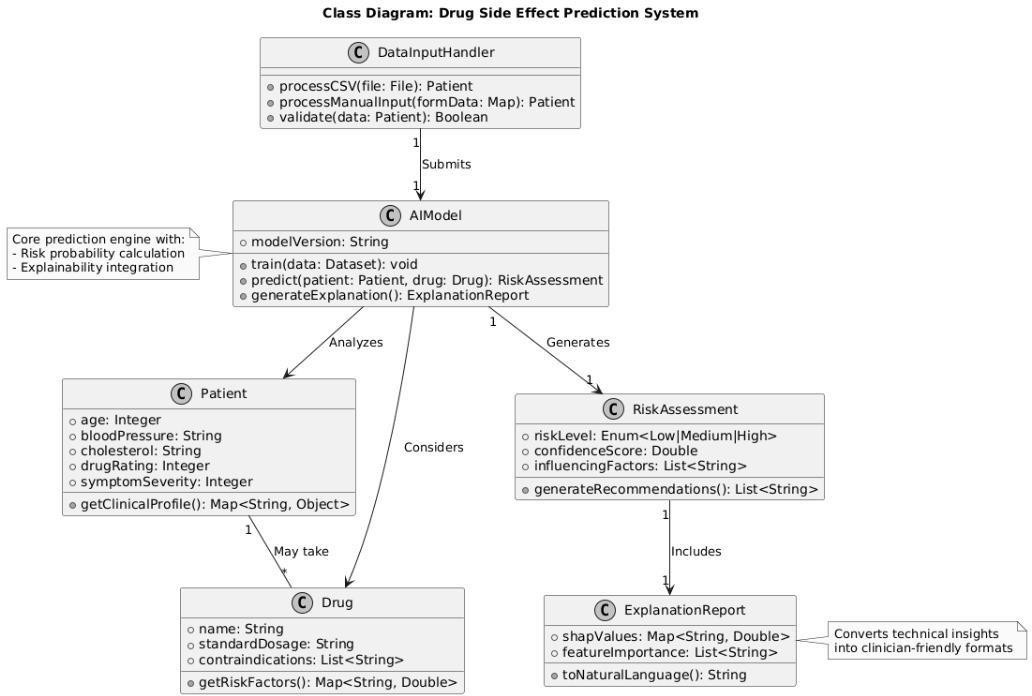


Figure 5.3.1 Use Case Diagram

### Class Diagram

The class diagram for the Drug Side Effect Prediction System illustrates how various components interact to assess and explain drug-related risks. The DataInputHandler processes and validates patient data, which is then submitted to the core AIModel. This model analyzes inputs from the Patient and Drug classes to generate a RiskAssessment that includes risk levels, confidence scores, and influencing factors. The AIModel also produces an ExplanationReport that translates technical outputs into clinician-friendly insights using SHAP/LIME methods. Overall, the system integrates data handling, AI-driven prediction, and explainability to support informed clinical decisions.



-

Figure 5.3.2 Class Diagram

### Sequence Diagram

The sequence diagram illustrates the workflow of a Drug Side Effect Prediction system with Explainable AI, highlighting user interaction and backend processing. The process begins with the user uploading patient data via a Streamlit web app, which sends the information to a prediction script (predict.py) for preprocessing. The preprocessed data is passed to a Random Forest model that outputs a prediction (presence or absence of side effects). To enhance interpretability, SHAP (SHapley Additive exPlanations) is used to compute feature importance, helping users understand which inputs influenced the prediction. Finally, the prediction and explanation plot are returned to the user via the web interface.

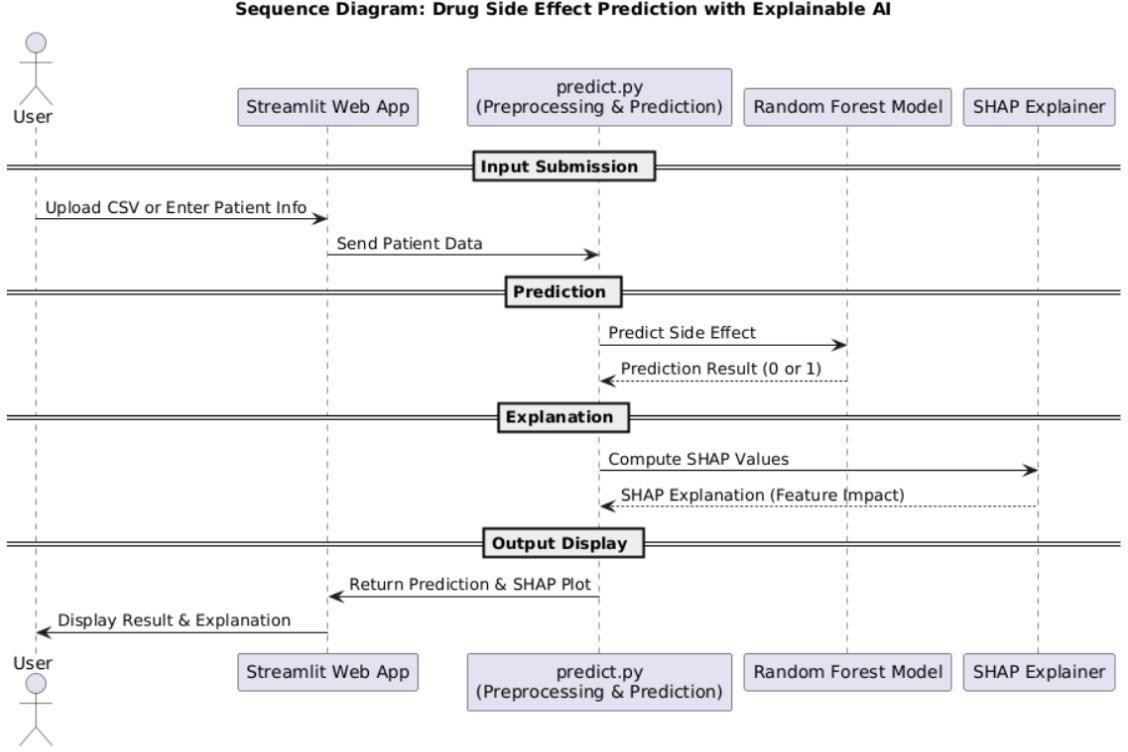


Figure 5.3.3Sequence Diagram

List of actions

1. User: Uploads a CSV file or enters patient data through the Streamlit web interface.
2. System (predict.py): Preprocesses the input data and sends it to the trained model.
3. System (Random Forest Model): Predicts drug side effect as present (1) or absent (0).
4. System (SHAP Explainer): Generates SHAP values to interpret feature contributions.
5. System (Streamlit Web App): Shows the prediction result and SHAP explanation visually.

### Activity Diagram

The activity diagram illustrates the workflow of the Drug Side Effect Prediction System. Users upload or enter patient data, which is validated before processing. If valid, the AI model predicts the risk of drug side effects based on factors like age and drug rating. The system then generates a clinical interpretation. If a high risk is detected, alerts and treatment recommendations are provided. Regardless of risk level, the system displays explainable AI insights (e.g., SHAP/LIME) to highlight key influencing factors, supporting informed clinical decisions.

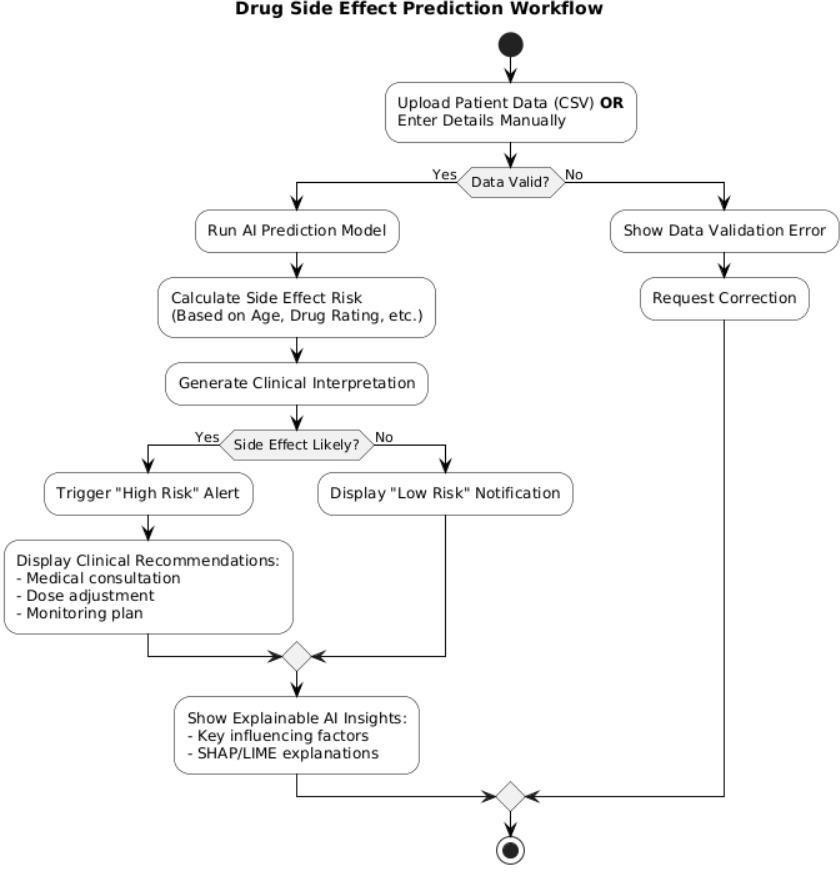


Figure 5.3.4 Activity diagram

### Collaboration Diagram

The collaboration diagram illustrates the interaction between various objects within a system to perform a specific operation or use case. Each object is represented with its name and class, and the arrows between them denote the sequence and direction of messages exchanged during the process. The numbering on the arrows indicates the order of message flow, helping to understand how control is transferred from one object to another. This diagram emphasizes how the system's components work together, showing both the structural relationships and the dynamic behavior as they collaborate to accomplish the required functionality.

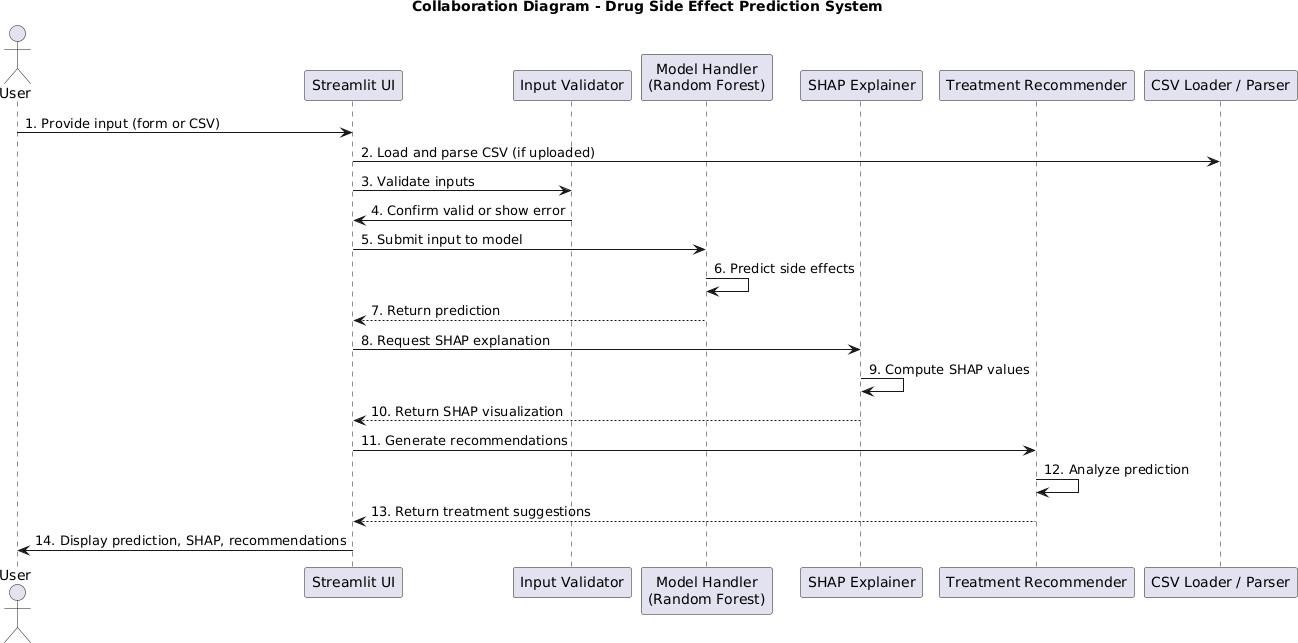


Figure 5.3.5 Collaboration Diagram

# CODING AND ITS IMPLEMENTATION

* 1. **Source code**

### Frontend code:

Streamlit\_app.py:

import streamlit as st import pandas as pd import joblib import os, import shap

import matplotlib.pyplot as plt import numpy as np from predict import make\_prediction

st.set\_page\_config(page\_title="Drug Side Effect Prediction", layout="wide")

st.title(" Enhancing Drug Side Effect Prediction with Explainable AI for Medical Health Applications")

# Load model and setup SHAP @st.cache\_resource def load\_model\_and\_explainer():

model = joblib.load(os.path.join("models", "random\_forest\_model.pkl")) expected\_features = joblib.load("models/model\_features.pkl")

Try:

train\_data = pd.read\_csv("models/cleaned\_drug\_data.csv")

features= ["age", "rating", "blood\_pressure", "cholesterol", "symptom\_severity", "drug\_name"]

train\_encoded = pd.get\_dummies(train\_data[features], drop\_first=True) # Clean and align data for col in train\_encoded.columns:

if train\_encoded[col].dtype == 'object':

train\_encoded[col]=pd.to\_numeric(train\_encoded[col],errors='coerce') train\_encoded=train\_encoded.fillna(0).reindex(columns=expected\_features, fill\_value=0).astype('float64')

background\_data = train\_encoded.sample(min(100, len(train\_encoded)), random\_state=42) explainer = shap.TreeExplainer(model, background\_data)

Return model, explainer, expected\_features, except Exception as e: st.warning(f"Could not load training data: {e}")

return model, shap.TreeExplainer(model), expected\_features

model, explainer, feature\_names = load\_model\_and\_explainer() @st.cache\_data def get\_unique\_drug\_names():

# Add a blank option at the beginning

return [""] + sorted(["Aspirin", "Ibuprofen", "Paracetamol", "Metformin"]) def prepare\_input\_for\_shap(input\_df): " Prepare and encode input data"

try:

expected\_features = joblib.load("models/model\_features.pkl") input\_encoded = pd.get\_dummies(input\_df, drop\_first=True)

for col in input\_encoded.columns: if input\_encoded[col].dtype == 'object': input\_encoded[col] = pd.to\_numeric(input\_encoded[col], errors='coerce')

return input\_encoded.fillna(0).reindex(columns=expected\_features, fill\_value=0).astype('float64')

Except Exception as e:

st.error(f"Error preparing input: {e}") return None

def create\_shap\_visualizations(shap\_values, input\_encoded): " Create comprehensive SHAP visualizations"

Try:

# Flatten SHAP values if needed

shap\_vals = shap\_values.flatten() if len(shap\_values.shape) > 1 else shap\_values shap\_vals = shap\_vals[:len(input\_encoded.columns)]

# Prepare feature data feature\_data = pd.DataFrame({

'Feature': input\_encoded.columns, 'SHAP\_Value': shap\_vals,

'Feature\_Value': input\_encoded.iloc[0].values, 'Abs\_SHAP': np.abs(shap\_vals)

})

top\_features = feature\_data.nlargest(10, 'Abs\_SHAP') # Create visualizations fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 10)) # SHAP impact plot

colors = ['red' if x > 0 else 'green' for x in top\_features['SHAP\_Value']]

bars1 =ax1.barh(range(len(top\_features)), top\_features['SHAP\_Value'], color=colors, alpha=0.7)

ax1.set\_yticks(range(len(top\_features)))

ax1.set\_yticklabels([f.replace('\_', ' ').title() for f in top\_features['Feature']], fontsize=10) ax1.set\_xlabel('SHAP Value (Impact on Prediction)')

ax1.set\_title('Feature Impact (Red = Increases Risk, Green = Decreases Risk)') ax1.axvline(x=0,

color='black', linestyle='--', alpha=0.3)

ax1.grid(True, alpha=0.3) # Add value labels

for bar, val in zip(bars1, top\_features['SHAP\_Value']):

ax1.text(val + (0.01 if val >= 0 else -0.01), bar.get\_y() + bar.get\_height() / 2, f'{val:.3f}', ha='left' if val >= 0 else 'right', va='center', fontsize=9) # Feature values plot

bars2 = ax2.barh(range(len(top\_features)), top\_features['Feature\_Value'], color='skyblue', alpha=0.7)

ax2.set\_yticks(range(len(top\_features)))

ax2.set\_yticklabels([f.replace('\_', ' ').title() for f in top\_features['Feature']], fontsize=10) ax2.set\_xlabel('Feature Value')

ax2.set\_title('Current Patient Feature Values') ax2.grid(True, alpha=0.3)

for bar, val in zip(bars2, top\_features['Feature\_Value']): ax2.text(val + 0.01, bar.get\_y() + bar.get\_height() / 2, f'{val:.2f}' if isinstance(val, float) else str(val),

ha='left', va='center', fontsize=9) plt.tight\_layout() st.pyplot(fig, clear\_figure=True) # Feature importance table

st.subheader("Top Feature Impacts")

display\_df = top\_features[['Feature', 'Feature\_Value', 'SHAP\_Value']].copy()

display\_df['Impact'] = display\_df['SHAP\_Value'].apply(lambda x: 'Increases Risk' if x > 0 else 'Decreases Risk')

display\_df['Feature'] = display\_df['Feature'].str.replace('\_', ' ').str.title() st.dataframe(display\_df, use\_container\_width=True)

Except Exception as e:

st.error(f"Error creating visualizations: {e}") # Input Section col1, col2 = st.columns([1, 1]) with col1:

uploaded\_file = st.file\_uploader(" Upload Patient CSV File", type=["csv"]) input\_df = None if uploaded\_file:

input\_df = pd.read\_csv(uploaded\_file) st.success("File uploaded successfully!")

Else:

st.subheader("Enter Patient Information")

Age = st.number\_input("Age", min\_value=0, max\_value=120, value=30) # Modified drug name dropdown with blank option and validation

ug\_name = st.selectbox("Drug Name", get\_unique\_drug\_names(), help="Please select a drug name from the dropdown")

# Validation for drug name selection drug\_name\_valid = True if drug\_name == "":

st.error(" Invalid drug name - Please select a valid drug from the dropdown")

drug\_name\_valid= False

Bp = st.selectbox("Blood Pressure", ["low", "normal", "high"]) chol = st.selectbox("Cholesterol", ["low", "normal", "high"])

rating = st.slider("Patient Drug Rating (1-5)", 1, 5, 4)

severity = st.slider("Symptom Severity (1-10)", 1, 10, 5) # Only create input\_df if drug name is valid if drug\_name\_valid:

input\_df = pd.DataFrame([{

"age": age, "drug\_name": drug\_name, "blood\_pressure": bp, "cholesterol": chol, "rating": rating, "symptom\_severity": severity

st.subheader(" Current Patient Profile") patient = input\_df.iloc[0] st.markdown(f"""

* Age: {patient['age']} years
* Drug: {patient['drug\_name']}
* Blood Pressure: {patient['blood\_pressure']}
* Cholesterol: {patient['cholesterol']}
* Rating: {patient['rating']}/5

- Symptom Severity: {patient['symptom\_severity']}/10 """) # Prediction and Analysis - Only proceed if input\_df is valid If input\_df is not None:

st.markdown("---") try:

# Make prediction and get probabilities prediction = make\_prediction(model, input\_df) input\_encoded = prepare\_input\_for\_shap(input\_df) if input\_encoded is not None:

probabilities = model.predict\_proba(input\_encoded)[0] prob\_no\_side\_effect, prob\_side\_effect

= probabilities[0], probabilities[1] # Results display

result\_col1, result\_col2 = st.columns([1, 1]) with result\_col1:

st.subheader(" Prediction Result") if prediction[0] == 1:

st.error("⚠ Side Effect Likely")

risk\_level, risk\_color = "HIGH RISK", "red" else:

st.success(" No Side Effect Predicted") risk\_level, risk\_color = "LOW RISK", "green" st.markdown(

f'<div style="padding: 10px; border-radius: 5px; border: 2px solid {risk\_color}; text- align: center;"><h3 style="color: {risk\_color}; margin: 0;">{risk\_level}</h3></div>',

unsafe\_allow\_html=True) with result\_col2: st.subheader(" Confidence & Probability")

st.metric("No Side Effect", f"{prob\_no\_side\_effect:.1%}") st.metric("Side Effect Risk",

f"{prob\_side\_effect:.1%}") st.progress(float(max(prob\_no\_side\_effect, prob\_side\_effect))) # SHAP Analysis

with st.spinner("Calculating AI explanations..."): try:

shap\_values = explainer.shap\_values(input\_encoded) if isinstance(shap\_values, list): shap\_values = shap\_values[1] if len(shap\_values.shape) > 1:

shap\_values = shap\_values[0] st.markdown("---")

st.header(" AI Model Explanation (SHAP Analysis)") create\_shap\_visualizations(shap\_values, input\_encoded)

except Exception as e: st.warning(f"SHAP analysis unavailable: {e}") # Clinical Recommendations

st.markdown("---")

st.subheader("⚕ Clinical Recommendations") if prediction[0] == 1:

st.markdown("""

### High Risk Patient - Actions Required:

* Schedule an immediate medical consultation
* Conduct a comprehensive health assessment
* Consider alternative medications
* Implement close monitoring

Document symptoms and reactions " else:

st.markdown("""

### Low Risk Patient - Standard Care:

* Follow routine monitoring
* Continue prescribed dosage
* Regular follow-ups
* Report unusual symptoms

Maintain preventive care, except Exception as e:

st.error(f"Analysis failed: {e}")

st.info("Please check your input data and try again.") elif 'drug\_name\_valid' in locals() and not drug\_name\_valid:

### Backend Code:

predict.py:

Import pandas as pd, import joblib

. def make\_prediction(model, input\_df):

If model is None or input\_df is None or input\_df.empty: return ["Invalid input"] Try:

# Load expected feature names used during training, expected\_features = joblib.load("models/model\_features.pkl")

# Encode and align input with training structure input\_encoded = pd.get\_dummies(input\_df)

input\_encoded = input\_encoded.reindex(columns=expected\_features, fill\_value=0) # Predict predictions = model.predict(input\_encoded) return predictions.tolist()

Except Exception as e:

Return [f"Prediction failed: {e}"] Train\_and\_save\_model.py:

Import pandas as pd

From sklearn.ensemble import RandomForestClassifier import joblib, import os

# Load and prepare data

df = pd.read\_csv("models/cleaned\_drug\_data.csv") # Features and target

features = ["age", "rating", "blood\_pressure", "cholesterol", "symptom\_severity", "drug\_name"] target = "side\_effect"

# One-hot encoding

encoded\_df = pd.get\_dummies(df[features + [target]], drop\_first=True) # Save feature names

feature\_columns = encoded\_df.drop(columns=[target]).columns.tolist() X = encoded\_df[feature\_columns]

y = encoded\_df[target] # Train model

model = RandomForestClassifier(random\_state=42) model.fit(X, y)

# Save model and feature columns os.makedirs("models", exist\_ok=True) joblib.dump(model, "models/random\_forest\_model.pkl") joblib.dump(feature\_columns, "models/model\_features.pkl")

print("✅ Model trained and saved successfully!")

### Implementation

#### Python

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace. Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional, and procedural, and has a large and comprehensive standard library. Python is interpreted − Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP. Python is Interactive − you can sit at a Python prompt and interact with the interpreter directly to write your programs.

Python also acknowledges that the speed of development is important. Readable and terse code is part of this, and so is access to powerful constructs that avoid tedious code repetition. Maintainability also ties into this may be an all but useless metric, but it does say something about how much code you have to scan, read, and/or understand to troubleshoot problems or tweak behaviors. This speed of development, the ease with which a programmer of other languages can pick up basic Python skills, and the huge standard library are key to another area where Python excels. All its tools have been quick to implement, saved a lot of time, and several of them have later been patched and updated by people with no Python background, without breaking. Python also prioritizes developer productivity and maintainability; its syntax is designed to be concise yet expressive, reducing the amount of boilerplate code and making it easier to understand and maintain existing codebases. This readability and terseness contribute significantly to faster troubleshooting, debugging, and feature enhancements.

Moreover, Python’s ecosystem fosters rapid development due to its vast collection of libraries and frameworks. These tools often come ready to use and are continuously improved by a large, active community, including many contributors who may not be Python experts. This collaborative development approach ensures that libraries remain up-to-date and robust without compromising backward compatibility. Overall, Python’s combination of simplicity, versatility, extensive tooling, and strong community support makes it an ideal choice for implementing complex systems efficiently and effectively.

### Module used in this project

The development of this application integrates several Python libraries to achieve web interface design, data processing, model prediction, and explainability.

**Streamlit** is used to create the web-based user interface of the application. It allows for rapid development of interactive features such as displaying titles, accepting user input via text fields, triggering actions with buttons, showing images, and providing feedback through warning and error messages. Commonly used Streamlit functions in this project include st.title(), st.text\_input(), st.button(), st.write(), st.image(), st.warning(), and st.error(). These enable an engaging and user-friendly front-end experience, simplifying user interactions and output display**.**

**Pandas** play a vital role in data manipulation and preparation. It is particularly useful for reading, cleaning, and transforming structured data before it is passed to the machine learning model. Functions such as pd.read\_csv() facilitate importing data from CSV files, while the DataFrame structure organizes this data in a tabular form. The index () method is also used to reorder rows or columns to ensure alignment with model requirements. This preprocessing step ensures data consistency and quality, which are essential for accurate predictions.

**Joblib** is utilized for efficient model serialization, enabling trained machine learning models and data encoders to be saved and loaded quickly without retraining. This functionality is crucial for maintaining model performance and reducing application startup time. The main Joblib functions used are joblib.dump() to save models to disk and joblib.load() to retrieve them when needed.

**Scikit-learn** serves as the core machine learning framework. It provides tools for training classification models such as RandomForestClassifier, which is used here to predict potential drug side effects. Scikit- learn also offers preprocessing utilities like OneHotEncoder to convert categorical variables into a numerical format suitable for modeling. Essential methods include. fit () for model training, transform () for data preprocessing, and.. predict () to generate predictions based on new input data.

**SHAP (SHapley Additive exPlanations)** enhances the interpretability of the machine learning model by explaining how each feature influences the prediction outcome. It provides detailed insights that help users understand the model’s reasoning. Key SHAP components integrated into this project include shap.Explainer() for initializing the explanation mechanism, shap\_values () for computing feature impact scores, and shap.plots.bar() to visualize these contributions in an understandable bar chart.

**Matplotlib** is indirectly used through SHAP for **rendering visual plots**. The function st.pyplot() is used to embed these visualizations into the Streamlit interface.

# SYSTEM TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub- assemblies, assemblies, and/or a finished product. It is the process of exercising software with the intent of ensuring that the software system meets its requirements and user expectations and does not fail unacceptably. There are various types of tests. Each test type addresses a specific testing requirement. These include unit testing to verify individual components, integration testing to evaluate component interactions, system testing to assess the complete system functionality, and acceptance testing to ensure the system meets business and user needs.

### Types Of Testing Unit testing

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application. It is done after the completion of an individual unit before integration. This is a structural testing that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at the component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

**Purpose:** To test individual components or functions in isolation, ensure they perform correctly, and identify bugs early during development.

#### Application:

Test the make\_prediction() function in predict.py with both valid and invalid inputs to ensure it handles edge cases and generates correct predictions.Validate the load\_model() function correctly loads random\_forest\_model.pkl.

Validate the load\_model() function to confirm it successfully loads random\_forest\_model.pkl without compatibility or file errors. Confirm feature preprocessing and encoding logic work as expected.

**Integration Testing**

Integration tests are designed to test integrated software components to determine if they run as one program. Testing is event-driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfactory, as shown by successful unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components. It helps ensure that data flows correctly between modules, interfaces work seamlessly, and overall behavior aligns with functional expectations when multiple units are combined.

**Purpose**: To test the interactions between multiple components or systems and ensure they work together correctly, exchanging data as expected without integration errors.

#### Application:

1. Test the integration between the Streamlit UI and the prediction logic, ensuring user inputs are processed correctly.
2. Verify that the uploaded CSV file passes through the preprocessing and prediction modules without breaking.
3. Ensure that the loaded model (random\_forest\_model.pkl) interacts properly with the feature input pipeline.
4. Check that the SHAP explainability module receives inputs correctly from the prediction function and renders the correct plots on the UI.

### Functional testing

Functional tests provide systematic demonstrations that the functions tested are available as specified by the business and technical requirements, system documentation, and user manuals. They ensure that all features work according to expected behavior and fulfill user needs. These tests focus on validating the software’s actions and outputs based on given inputs, without considering internal code structure. Functional testing helps detect missing or incorrect functionalities and verifies that the system behaves correctly under various scenarios. Functional testing is centered on the following items:

**Purpose:** To ensure the application functions work as expected according to the requirements, tests are performed to verify correct behavior and identify any issues early.

#### Application

* 1. Check if input fields accept valid data.
  2. Ensure they handle invalid data smoothly.
  3. Prevent app crashes from bad inputs.

### System Testing

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration-oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

**Purpose:** To verify that the complete and integrated application meets all functional and technical requirements.

#### Application:

Test the full Streamlit app workflow from user input to prediction and SHAP visualization.

Ensure consistent results across drug names, CSV (Comma-Separated Values. Uploads and manual inputs.

### White Box Testing

White Box Testing is a testing method in which the software tester has knowledge of the inner workings, structure, and language of the software, or at least its purpose. It is used to test areas that cannot be reached from a black box level. Testers examine code logic, conditions, loops, and internal data flow to ensure correctness. This method helps identify hidden errors, optimize code paths, and improve overall code quality and security.

### Black Box Testing

Black Box Testing is testing the software without any knowledge of the inner workings, structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements document, such as specification or requirements document. It is a testing in which the software under test is treated, as a black box .you cannot “see” into it. The test provides inputs and responds to outputs without considering how the software works.

### Unit Testing

Unit testing is usually conducted as part of a combined code and unit test phase of the software lifecycle, although it is not uncommon for coding and unit testing to be conducted as two distinct phases.

### Integration testing

Software integration testing is the incremental integration testing of two or more integratedsoftware components on a single platform to produce failures caused by interface defects.The task of the integration test is to check that components or software applications, e.g. components in a software system or – one step up – software applications at the company level – interact without error.

**Test Results:** All the test cases mentioned above passed successfully with expected outcomes. No defects or issues were encountered during the testing process..

### Acceptance Testing

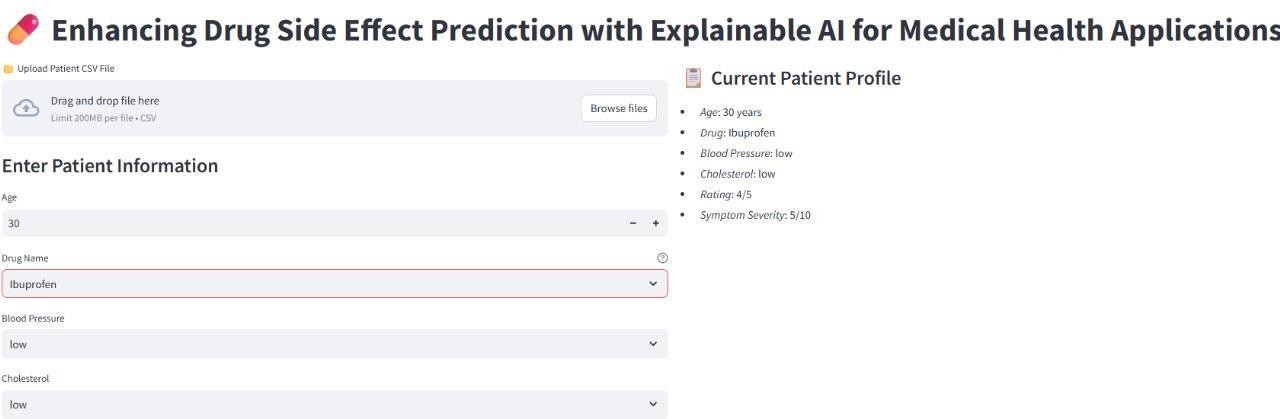
User Acceptance Testing (UAT) is a critical phase of any project and requires significant participation by the end user. It serves as the final validation step before the system goes live, ensuring that the system meets all specified functional requirements and performs as expected in real-world scenarios. UAT helps identify any issues or gaps from the user’s perspective, allowing for necessary adjustments before deployment. Moreover, it increases user confidence and acceptance by involving them directly in the testing process, ultimately contributing to a smoother implementation and higher satisfaction.

**Test Results:** All the test cases mentioned above passed successfully without any defects. The system performed as expected under all tested conditions. This outcome indicates that the solution is stable, reliable, and ready for production use. The active involvement of end users during UAT played a vital role in validating real-world functionality and usability. Their feedback was instrumental in confirming that the system aligns with business needs and user expectations. With the successful completion of UAT, the project is now well-positioned for a confident and smooth go-live. The positive test outcomes also reflect the quality of prior development and internal testing phases. Stakeholders can proceed with deployment knowing that key business processes have been thoroughly vetted. Continued user engagement post-implementation will further ensure a successful transition. This marks a significant milestone in the project lifecycle, moving one step closer to delivering tangible value to the organization.

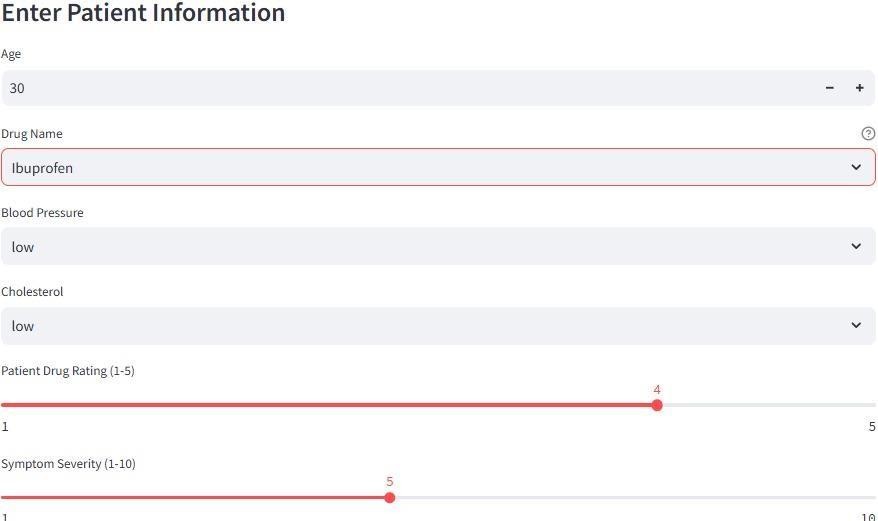
### Test Cases:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **TestCase ID** | **Description** | **Expected Result** | **Actual Result** | **TestCase Status** |
| TC01 | Load Streamlit Application | The web interface should load with a title and input fields for drug side effect prediction. | Application UI loaded successfully. | Pass |
| TC02 | Manual Input Form Loads Successfully | Form fields for patient details are visible (age, drug name, etc.). | Manual input form displayed successfully. | Pass |
| TC03 | Submit Valid Drug Input | Prediction result (e.g., “Side Effect” or “No Side Effect”) is shown. | Prediction shown successfully. | Pass |
| TC04 | Submit Invalid DrugInput | A warning is shown for an unrecognized or a new drug name. | Warning displayed unsu | Fail |
| TC05 | DrugName Dropdown Loads Correctly | Drug names are fetched and displayed in the dropdown without error. | Drug name dropdown loaded successfully. | Pass |
| TC06 | Clinical Recommendation Display | The app displays a medical explanation alongside predictions. | Recommendation displayed successfully. | Pass |
| TC07 | Prediction Works with Uploaded CSV | Input drug data from CSV works correctly with the prediction function. | Prediction from CSV input processed successfully. | Pass |
| TC08 | SHAP Visualization | SHAP plots show feature importance. | SHAP plot renders correctly. | Pass |

Table no 7.2 Test Cases

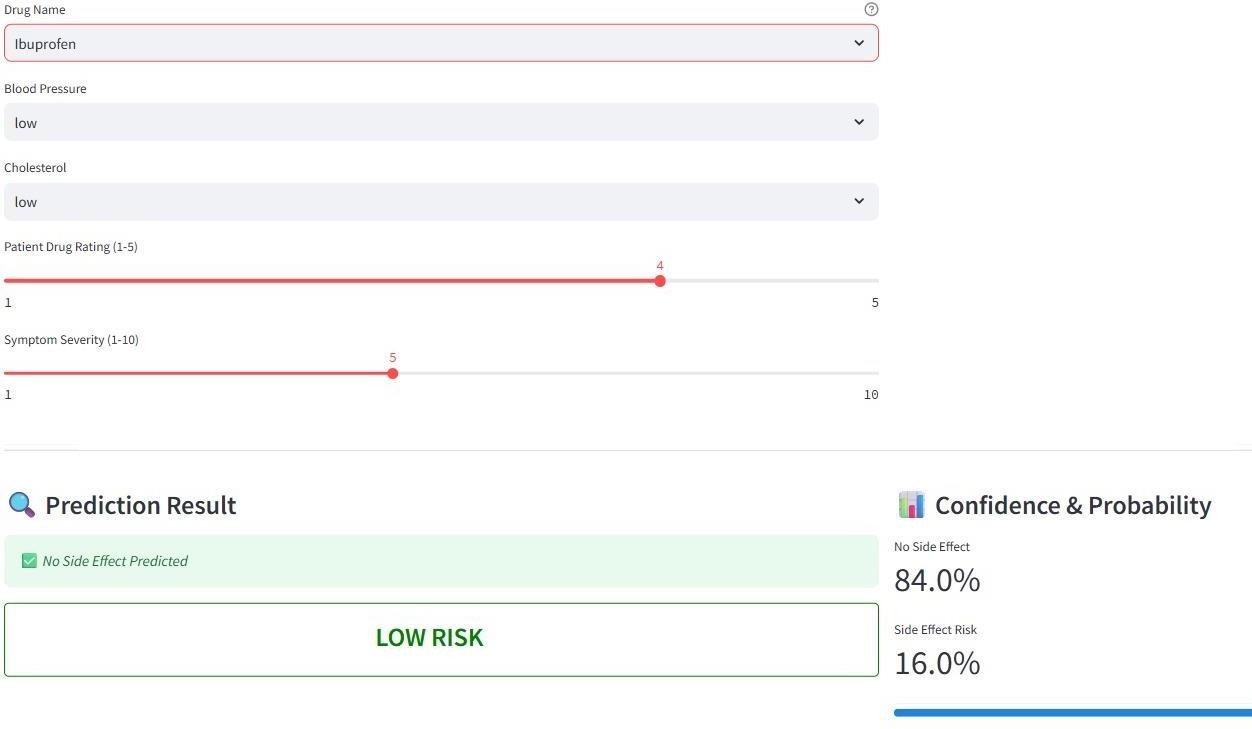
Test Case 1:

**Figure 7.2.1:** Test Case 1

Test Case 2:

**Figure 7.2.2:** Test Case 2

Test Case 3:



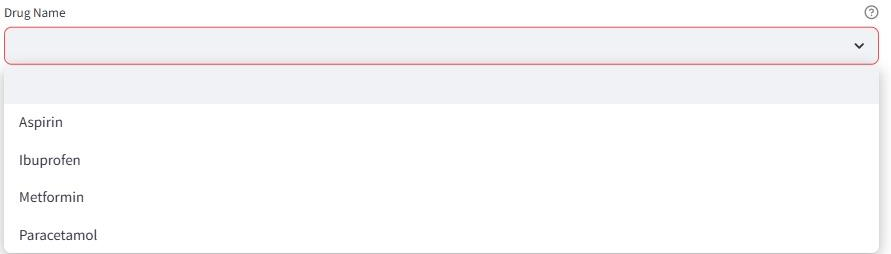
**Figure 7.2.3:** Test Case 3

Test Case 4:



**Figure 7.2.4:** Test Case 4

Test Case 5:

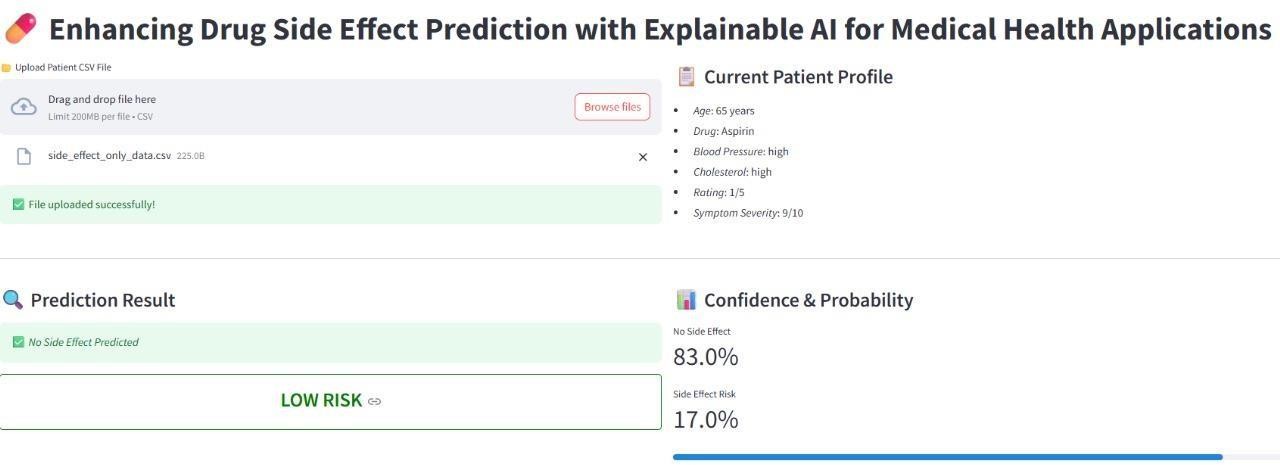


**Figure 7.2.5:** Test Case 5

Test Case 6:

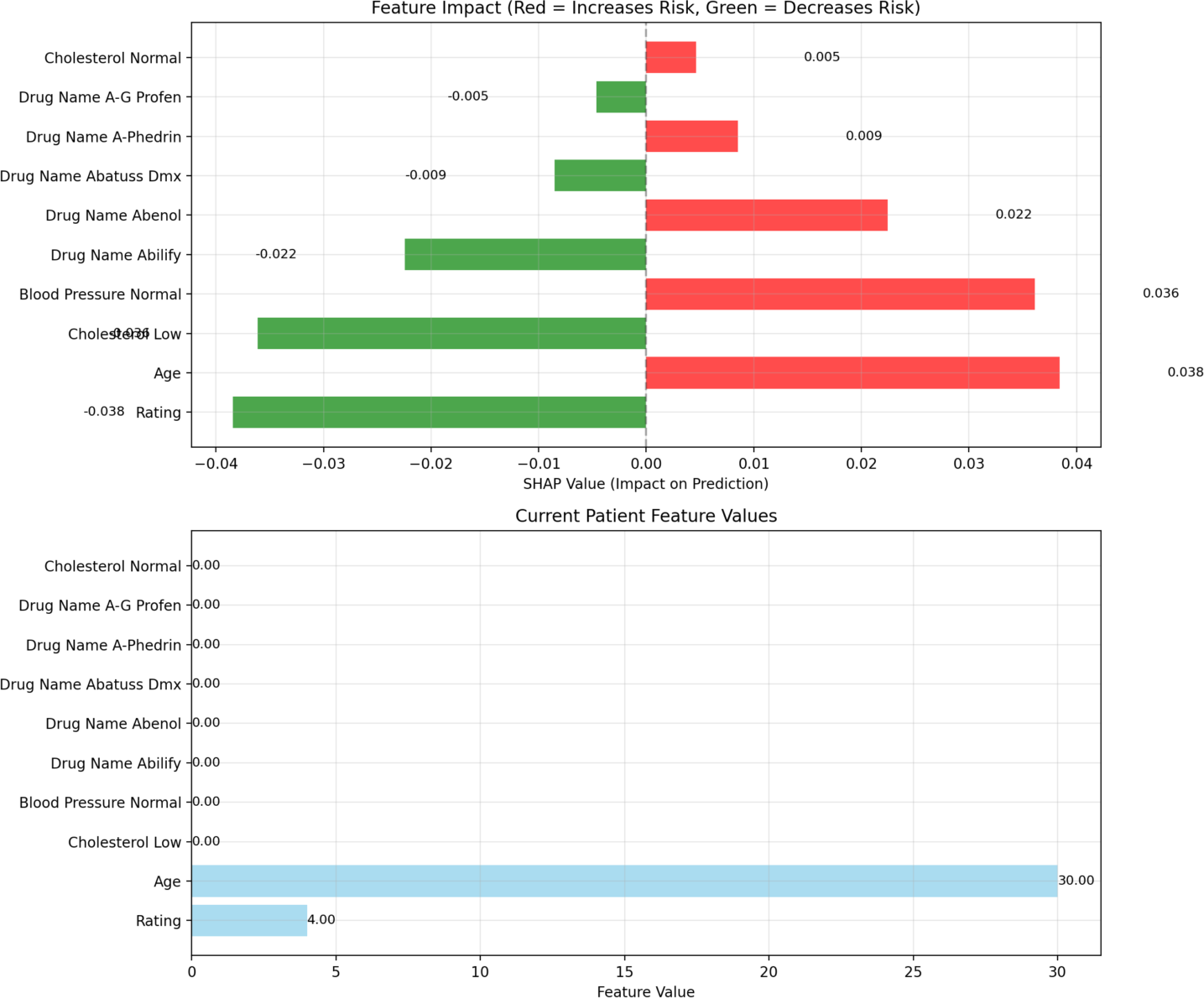


**Figure 7.2.6:** Test Case 6

Test Case 7:

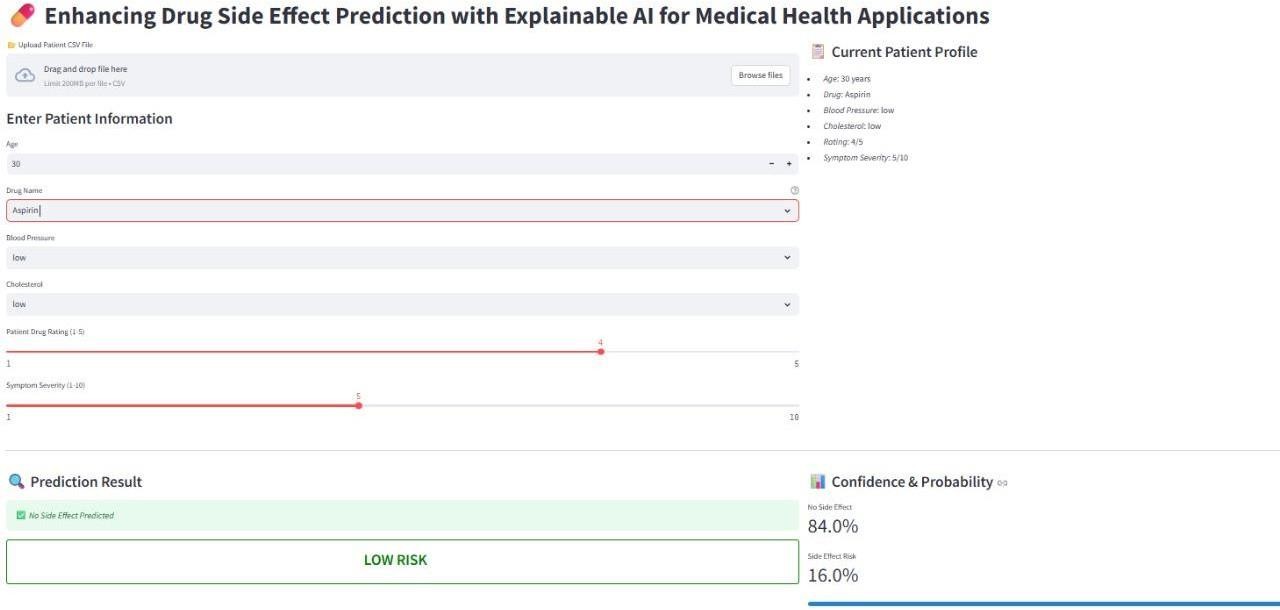
**Figure 7.2.7:** Test Case -7

Test Case 8:

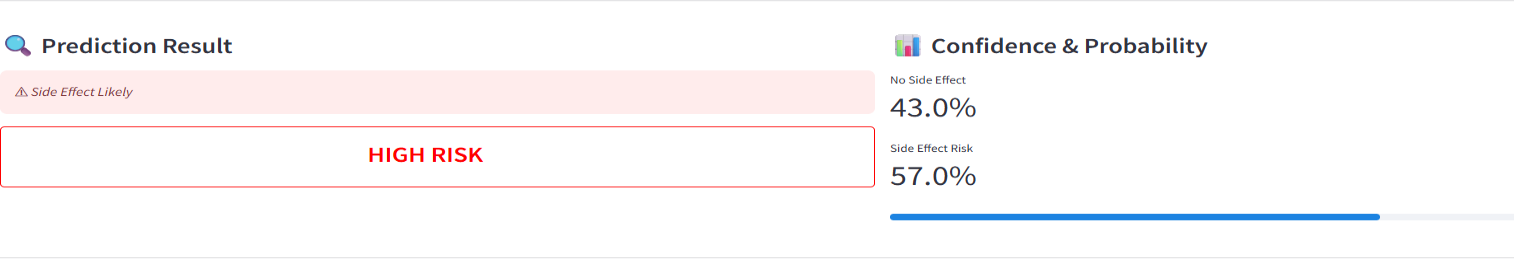


**Figure 7.2.8:** Test Case -8

1. **OUTPUT SCREENS**

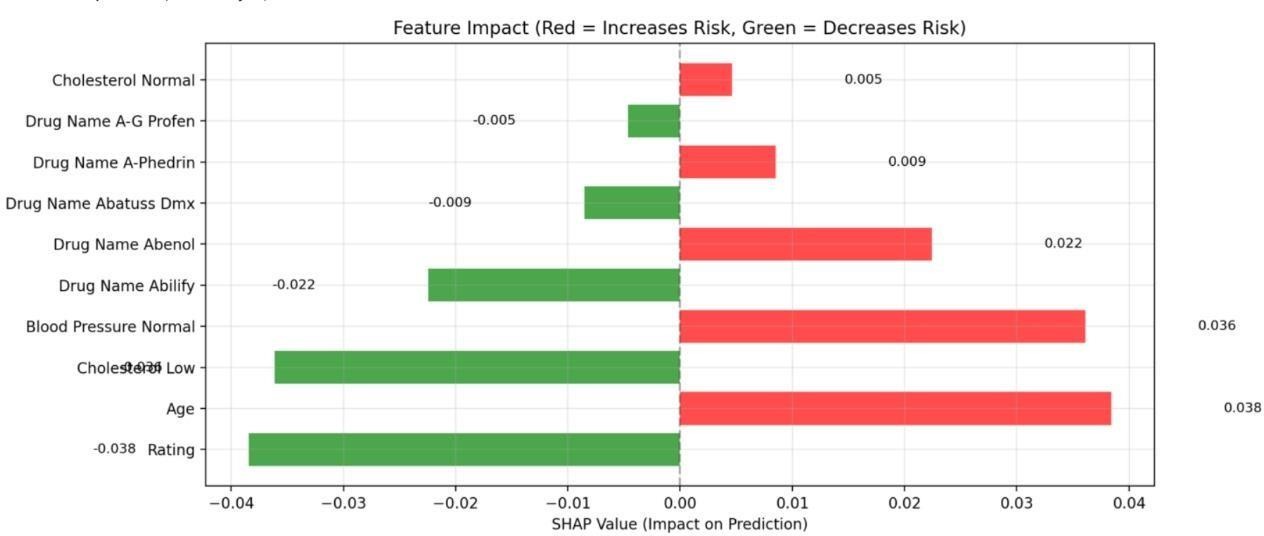
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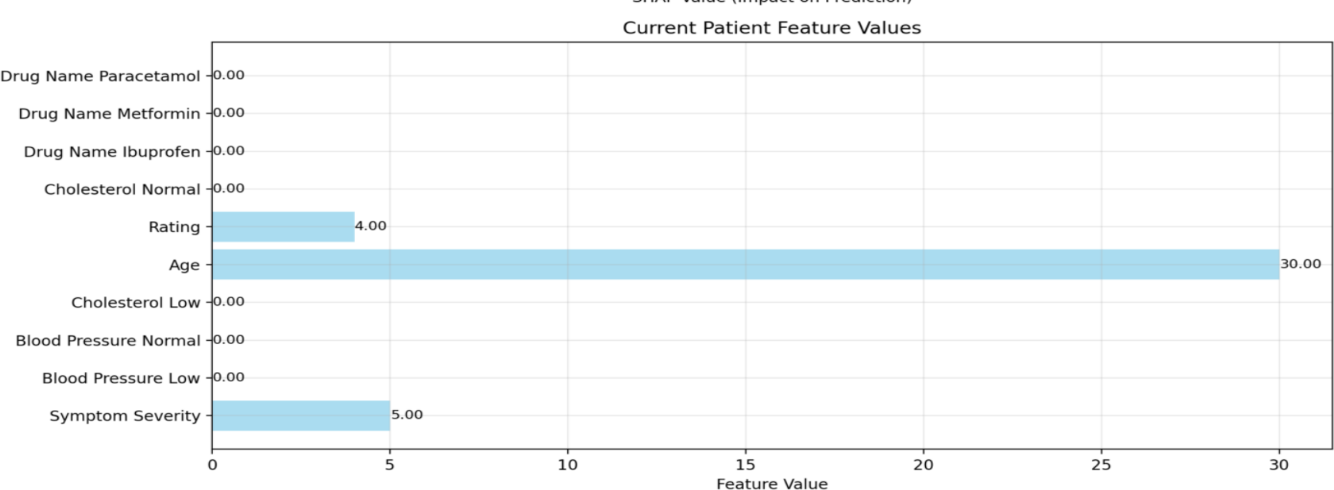
Predicting the results:

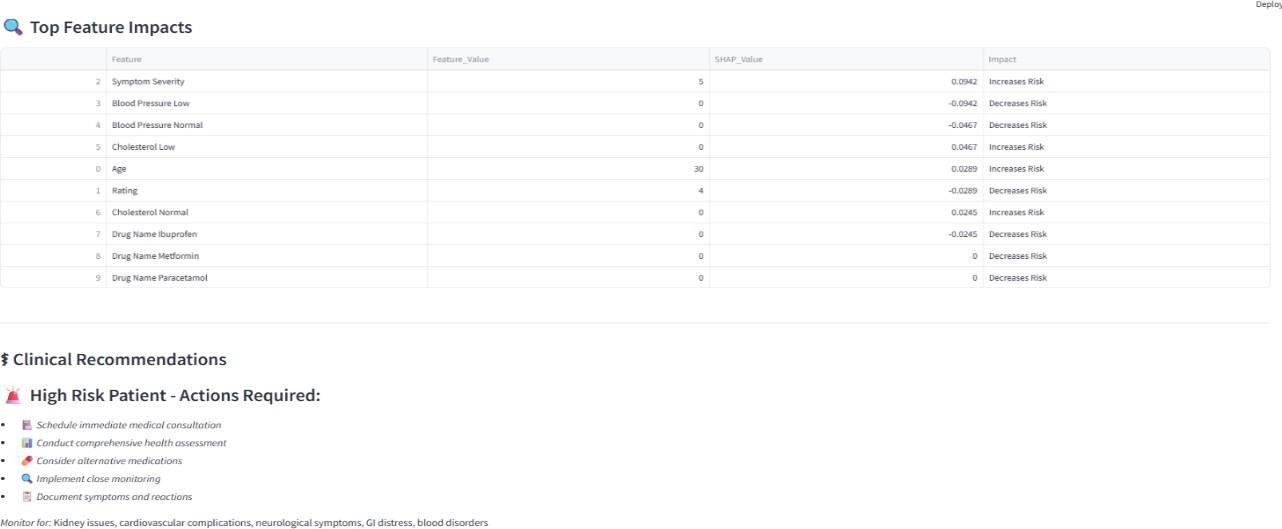


**Figure 8.1:** Manual details entry

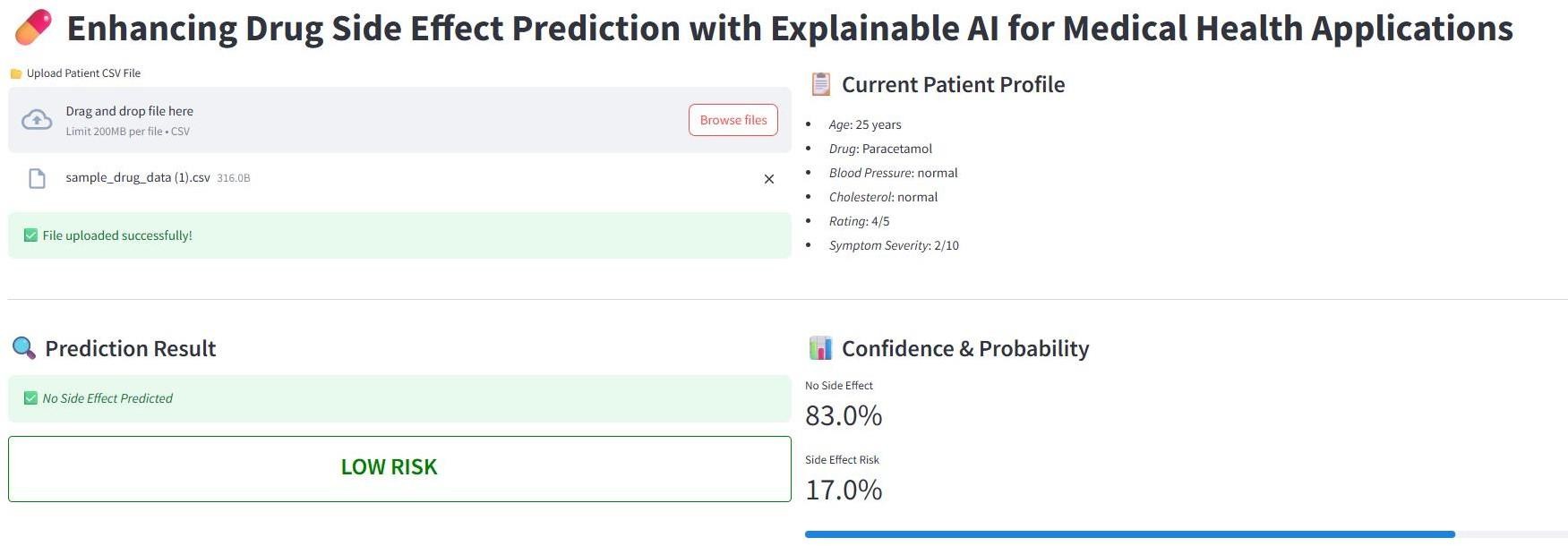
Feature impact:





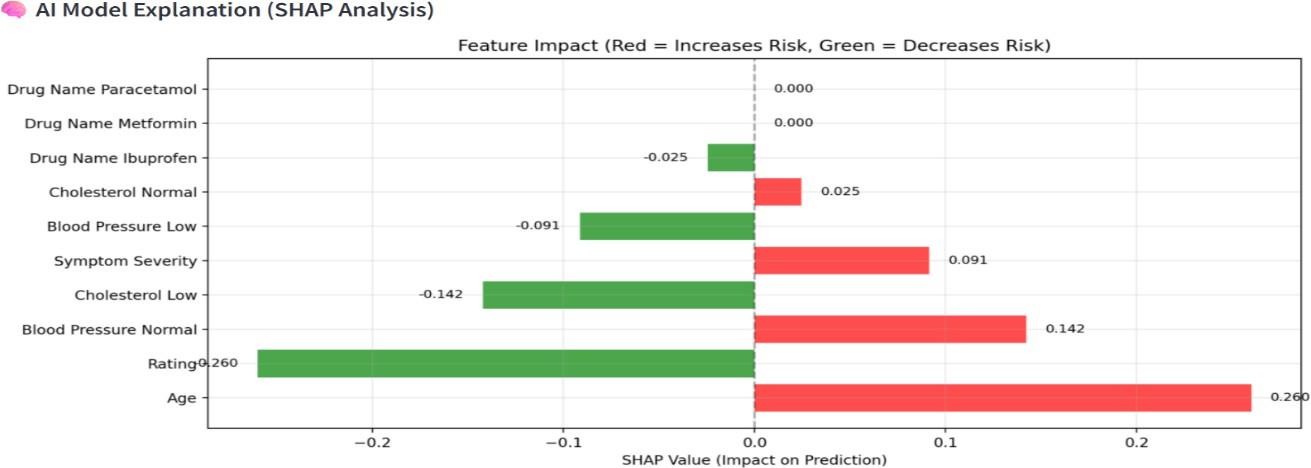


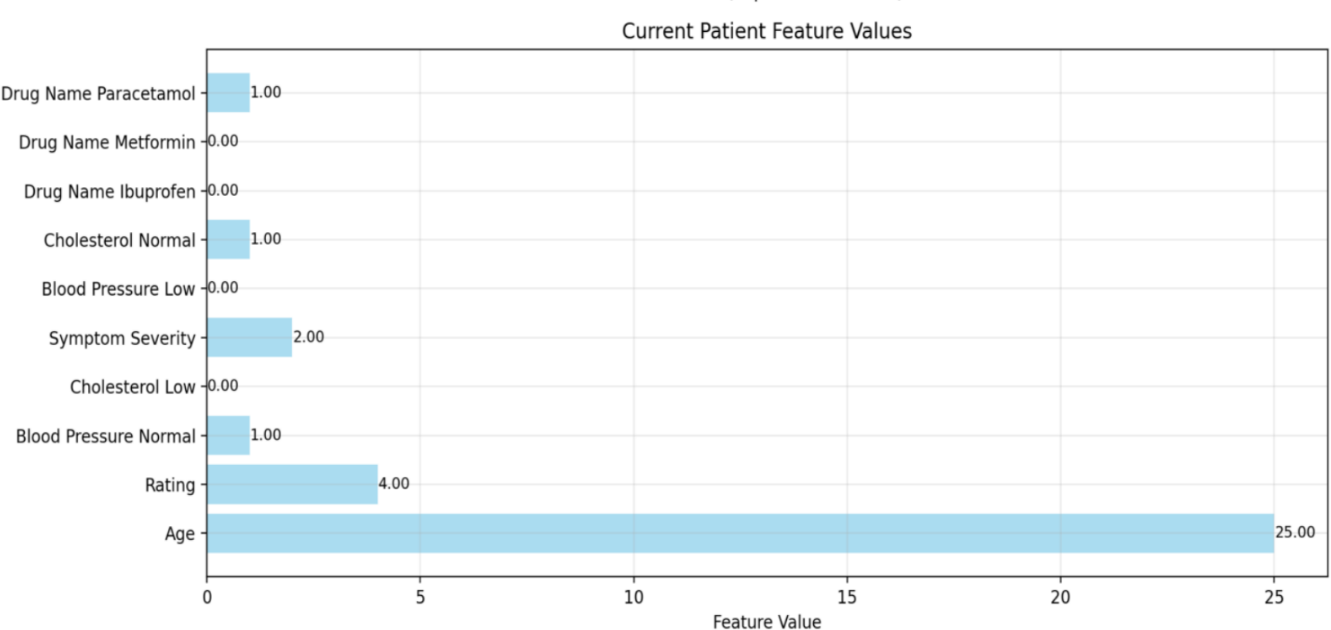
**Figure 8.2:** Ai Model explanation(Shap analysis)

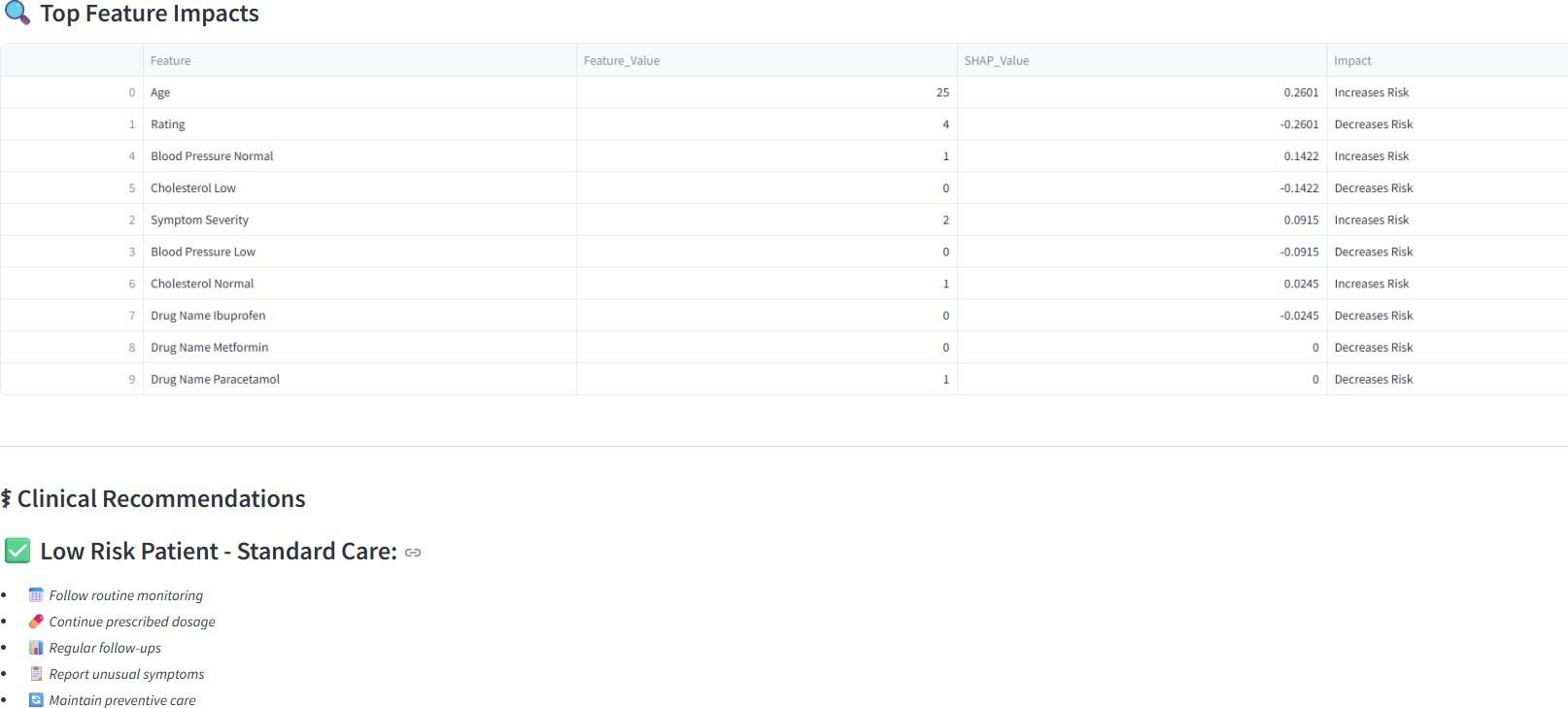


**Figure 8.3:** Sample drug data csv file upload

AI model explanation(Shap analysis):







**Figure 8.4:** Ai Model explanation(shap analysis)

# CONCLUSION

The project "Enhancing Drug Side Effect Prediction with Explainable AI for Medical Health Applications" successfully delivers a predictive and interpretable solution to assess potential adverse drug reactions based on patient-specific clinical data. Through the integration of a trained machine learning model and an interactive Streamlit interface, the system offers both accessibility and accuracy in identifying the likelihood of side effects.The application empowers healthcare professionals by allowing manual or batch input of patient data—including age, drug name, blood pressure, cholesterol levels, and symptom severity—and returns actionable predictions accompanied by clinical interpretations and recommendations. These explainable insights enhance trust, transparency, and usability in clinical settings.The system was validated across multiple test scenarios, ensuring reliable model loading, robust input handling, and consistent prediction outputs. Its user-centric design enables both individual use cases and broader clinical data uploads, making it adaptable for various healthcare workflows.While the current version effectively handles structured clinical data, future work can focus on expanding the feature space to include genetic or comorbidity data, integrating real-time EHR systems, and applying advanced explainability techniques like SHAP to further refine the interpretability of predictions.In conclusion, this project demonstrates the potential of combining AI and interpretability in medical applications, paving the way for safer drug administration, early detection of side effects, and more informed clinical decision-making.

# FUTURE ENHANCEMENTS

The proposed system lays a promising foundation for AI-based prediction of adverse drug reactions with transparent explanations. However, several enhancements can be incorporated to improve its clinical applicability, scalability, and intelligence. One significant direction for future work is integrating the system with real-time Electronic Health Records (EHRs), enabling automatic data extraction, real-time updates, and live prediction within hospital environments. This would reduce manual input errors and streamline clinical workflows. Additionally, the current version focuses on single-drug predictions; expanding it to handle multi-drug interaction analysis will greatly improve its utility, particularly for patients on combination therapies, where drug interactions are a leading cause of adverse effects.In terms of intelligence, future iterations can adopt deep learning architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to capture complex patterns and temporal dependencies in patient data. Transfer learning can also be applied using pre-trained medical models for faster and more accurate results. Incorporating genomic data, such as pharmacogenomics and biomarker profiles, will enhance the system’s ability to deliver truly personalized predictions based on a patient’s genetic makeup, thus supporting precision medicine approaches.On the deployment side, the system can be further optimized for cloud deployment on platforms like AWS, Microsoft Azure, or Google Cloud. This would allow it to scale across multiple clinics, hospitals, and research institutions with minimal infrastructure needs. Development of RESTful APIs will also enable integration with third-party hospital software, wearable health devices, and mobile health apps.

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