CHAPTER-1

INTRODUCTION

In medical emergencies, timely and accurate treatment decisions are critical to saving lives and improving patient outcomes. One of the most important aspects of emergency care is the appropriate prescription of drugs based on a patient's clinical profile. The complexity of human physiology, coupled with the variability in patient characteristics such as age, sex, blood pressure, cholesterol levels, and electrolyte balance, makes drug selection a challenging task. Traditionally, drug prescription decisions rely heavily on the experience and judgment of medical professionals, which, while effective, may not always be optimal—especially in high-pressure environments with limited time for detailed analysis.

With the increasing availability of healthcare data, there is a growing demand for intelligent systems that can support clinical decision-making by analyzing patient information and recommending suitable treatments. Automating drug recommendations can reduce the risk of human error, standardize treatment decisions, and improve the efficiency of medical response in emergency settings. By leveraging data-driven insights, such systems can help ensure that patients receive the most effective medication tailored to their specific health parameters. The use of machine learning in this domain offers a promising avenue for enhancing the precision and speed of medical interventions, ultimately contributing to better healthcare delivery.

In emergency medical situations, the need for rapid and precise treatment is paramount, as every second can significantly influence a patient's chances of survival and recovery. Among the many critical decisions healthcare providers must make, selecting the right medication stands out as a key component in ensuring effective treatment. However, determining the most appropriate drug for a patient is far from straightforward. Human biology is inherently complex, and individual differences in factors like age, gender, vital signs, cholesterol levels, and electrolyte status add further layers of complexity to the decision-making process. Traditionally, physicians have relied on their clinical experience and intuition to prescribe drugs, particularly under the pressure of time constraints and high-stakes scenarios. While this approach has served well in many cases, it is inherently limited by human variability and cognitive load, which may result in suboptimal choices.

In recent years, the proliferation of digital health records and biomedical data has created new opportunities for technological advancements in clinical practice. There is a growing recognition of the potential benefits that intelligent decision-support systems can bring to emergency medicine. These systems, powered by data analytics and machine learning algorithms, can rapidly analyze a patient's clinical information and suggest the most appropriate medication based on patterns learned from vast datasets. Such tools can serve as a valuable second opinion or real-time assistant, offering recommendations that are both personalized and evidence-based.

Fig 1: Drug

By integrating machine learning into emergency care workflows, hospitals can minimize human error, ensure consistency in treatment protocols, and accelerate the overall decision-making process. This not only enhances the safety and quality of care but also optimizes resource utilization in fast-paced healthcare environments. Ultimately, the implementation of automated drug recommendation systems holds the promise of transforming emergency medicine—making it more data-informed, responsive, and aligned with the individual needs of patients

In the realm of healthcare, especially during medical emergencies, timely and accurate treatment decisions are critical to saving lives and improving patient outcomes. In such high-pressure situations, every second counts, and even minor delays or errors in judgment can lead to severe consequences. One of the most crucial aspects of emergency care is the selection and administration of the correct medication based on a patient's specific health profile. However, determining the most appropriate drug is not always straightforward. The complexity of human physiology, coupled with variations in individual patient factors such as age, gender, blood pressure, cholesterol levels, sodium and potassium balance, and underlying health conditions, makes drug selection a highly sensitive and challenging task.

Traditionally, medical professionals rely on their expertise, clinical experience, and standard treatment guidelines to make prescription decisions. While these approaches have proven effective, they may not always be optimal—especially in situations where time is limited, data is incomplete, or multiple treatment options must be considered quickly. In emergency settings, doctors are required to make split-second decisions that ideally should be supported by data and evidence-based analysis. However, the cognitive load and fast pace often limit the ability to consider all variables in depth. This opens the door for intelligent systems that can support clinical decision-making and reduce the burden on healthcare providers.

With the rise of digital healthcare and the availability of large-scale medical data, the integration of machine learning (ML) techniques has shown immense promise in transforming how treatment decisions are made. Machine learning algorithms have the ability to learn complex patterns from historical data and predict outcomes based on current inputs. In the context of emergency drug prescription, ML models can be trained on large datasets containing patient conditions, drug responses, adverse reactions, and treatment success rates. These models can then be used to recommend the most suitable drug for a new patient, thereby enhancing both the speed and accuracy of the decision-making process.

Furthermore, ML-based drug recommendation systems can help standardize care, reduce the risk of human error, and ensure that each patient receives a treatment tailored to their individual health parameters. This is particularly useful in resource-limited or overburdened healthcare environments where medical staff may not have access to specialized knowledge or time for detailed analysis. Moreover, such systems can continuously improve over time by learning from new data, making them adaptable and future-proof.

In this project, we aim to design and implement a Drug Recommendation System for Medical Emergencies using a variety of machine learning algorithms including Decision Trees, Logistic Regression, Random Forests, Naive Bayes, Support Vector Machines (SVM), LSTM, and a Stacking Classifier. The system takes input from users such as a patient's age, sex, blood pressure, cholesterol, and electrolyte levels, and predicts the most appropriate drug.

1.1 Objective:

The objective is to design a drug recommendation system using machine learning and deep learning techniques to support clinical decision-making in medical emergencies. The system will preprocess patient data and evaluate multiple algorithms, including Logistic Regression, Naive Bayes, Decision Tree, Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM). An ensemble method using a Stacking Classifier that combines Decision Tree, Random Forest, and LightGBM will also be implemented to enhance the accuracy and reliability of drug prediction.

1.2 Scope of the project:

The project aims to develop an intelligent drug recommendation system tailored for use during medical emergencies, where rapid and accurate decision-making is crucial. By leveraging machine learning and deep learning techniques, the system is designed to analyze structured patient data—such as age, sex, blood pressure, cholesterol levels, and electrolyte balance—and generate precise drug recommendations. It addresses the limitations of traditional manual prescription methods, which are often prone to delays and inaccuracies, especially in high- pressure emergency scenarios. The scope of the project encompasses the integration of multiple models including Logistic Regression, Decision Tree, Random Forest, Naive Bayes, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM), alongside an ensemble Stacking Classifier that combines Decision Tree, Random Forest, and LightGBM. This approach enhances prediction accuracy and robustness. Additionally, the system is built with scalability and usability in mind, featuring a web-based interface developed using Flask, complete with secure user authentication. The system is intended not only to support clinicians with data-driven insights but also to be extendable with future improvements such as integration with electronic health records (EHRs), real-time monitoring, and explainable AI modules.

CHAPTER-2

LITERATURE SURVEY

The application of artificial intelligence (AI) and machine learning (ML) in healthcare has gained significant momentum, particularly in the areas of emergency medicine, clinical decision support, and drug recommendation. As patient data becomes increasingly digitized and voluminous, the need for intelligent systems that can offer real-time, personalized, and accurate decisions has never been more pressing. A number of studies have tackled this challenge through innovative approaches ranging from deep learning to ensemble methods and large language models.

A notable advancement in this field was presented by Omana *et al.* (2025), who introduced a personalized drug recommendation system that combines Wasserstein Autoencoders (WAEs) with a Weighted Feed Forward Neural Network, coined WAES-ADR [1]. This dual-component architecture not only enhances drug recommendation accuracy but also facilitates the early detection of adverse drug reactions (ADRs). The model achieved an ADR detection accuracy of 96.04%, surpassing existing systems by over 15% and demonstrating significant improvements across precision, recall, and F1-score metrics. By leveraging the robust representational power of WAEs, the system adeptly models complex and heterogeneous healthcare data, setting a benchmark for personalized pharmacotherapy and patient safety.

In parallel, the utility of conventional machine learning algorithms in drug recommendation has also been investigated. While deep learning models tend to dominate the discourse, simpler algorithms like Support Vector Machines (SVM), XGBoost, and Multinomial Naïve Bayes (NB) have proven to be both effective and computationally efficient. One comparative study evaluated these three models using a dataset from the UCI ML repository and found that XGBoost consistently outperformed the others in terms of classification accuracy and robustness [2]. These results reinforce the value of ensemble-based learning techniques in structured medical data contexts and highlight the trade-off between model interpretability and complexity.

Beyond drug recommendation, machine learning has been applied to optimize emergency triage systems, especially in pediatric care. Traditional triage methods, which often rely on subjective clinical judgment, can be inconsistent and prone to error. Aljubran *et al.* (2025) addressed this issue by employing a variety of ML techniques—including ensemble, regularization, and dimensionality reduction algorithms—to analyze pediatric emergency department records [3]. After rigorous data preprocessing, the study retained over 18,000 cases and revealed that ensemble models, particularly CatBoost, delivered superior results with an F1-score of 90%. Impressively, the model maintained zero critical misclassifications, demonstrating its suitability for high-stakes triage decisions and potential for real-world deployment in emergency departments.

Further pushing the frontier of clinical decision support, Han and Choi (2024) proposed a Large Language Model (LLM)-based multi-agent system that aids triage and treatment planning using the Korean Triage and Acuity Scale (KTAS) [4]. Built on Llama-3-70b and orchestrated through CrewAI and Langchain, the system emulates four essential emergency department roles: Triage Nurse, Emergency Physician, Pharmacist, and ED Coordinator. It integrates RxNorm for standardized medication references and has been validated using the Asclepius dataset. The results show improved accuracy in triage and clinical planning over baseline models, underscoring the potential of LLMs to orchestrate dynamic, role-based decision-making in real- time hospital environments. This study is a landmark in the integration of multi-agent systems and LLMs into healthcare infrastructure.

Complementing these technological strides, Smith *et al.* (2025) provided a comprehensive primer for healthcare professionals seeking to understand AI applications in emergency medicine [5]. The paper covers key principles of AI, potential use cases—ranging from staffing optimization to disease progression prediction—and addresses barriers such as model bias, interpretability, and data privacy. Importantly, the authors offer a resource-rich pathway for non- experts to become informed users of AI tools, facilitating broader adoption and ethical implementation in clinical settings.

In synthesis, these studies collectively underscore the transformative potential of AI in healthcare. From enhancing drug safety and personalization through advanced neural architectures [1], to improving efficiency via ensemble learning methods [2], to bolstering accuracy in pediatric triage systems [3], and integrating LLM-driven multi-agent collaboration in emergency settings [4], the field is rapidly evolving. However, as highlighted by Smith *et al.* [5], successful integration into real-world settings requires not only technological sophistication but also clinician education, model transparency, and regulatory oversight. Future research should focus on building explainable, scalable, and clinically validated models that address these multidisciplinary challenges.

Zhang et al. (2024) introduced a hybrid deep learning framework called MedFusionNet, specifically designed for clinical decision support in high-pressure emergency room scenarios [6]. By fusing Convolutional Neural Networks (CNNs) for imaging data and Bidirectional LSTM networks for EHR sequences, the system provides real-time diagnostic suggestions and treatment options. Tested on the MIMIC-IV dataset, MedFusionNet achieved a diagnostic accuracy of 94.3% for cardiovascular emergencies. The model's attention mechanism allows for partial interpretability by highlighting influential data points in decision-making, thereby bridging the gap between black-box AI and clinical transparency.

Lee and Kumar (2025) presented a graph neural network-based model named DrugGraphRec, which utilizes patient-drug interaction graphs for personalized medication suggestions [7]. By encoding both drug similarity and patient history as graph embeddings, the model captures complex relational patterns often missed by traditional matrix factorization methods. Evaluated on a large-scale EHR dataset from a Korean hospital network, DrugGraphRec achieved a mean average precision (MAP) of 0.82, outperforming Transformer-based baselines and demonstrating strong generalization across demographic subgroups. This work highlights the promise of graph-based reasoning in pharmacological decision-making.

Patel et al. (2024) explored federated learning frameworks to build privacy-preserving models for emergency health diagnostics across multiple hospitals [8]. Their proposed Federated DenseNet was trained collaboratively without transferring raw patient data, thereby adhering to strict data governance norms such as HIPAA and GDPR. Despite decentralized training, the model's diagnostic accuracy only dropped by 1.2% compared to centralized training, showcasing federated learning as a viable method for building robust and secure AI healthcare models. The study also presented strategies to mitigate inter-hospital data heterogeneity using domain adaptation layers.

Nguyen and Abouelmagd (2025) developed a reinforcement learning-based drug recommendation system that adapts treatment strategies based on patient response over time [9]. Using a Deep Q-Network (DQN) approach, the system dynamically adjusts prescriptions for chronic diseases such as hypertension and diabetes, considering both short-term efficacy and long-term side effects. Simulation tests on synthetic patient models indicated a 17% improvement in health outcomes over rule-based systems. This research underscores the potential of sequential decision-making algorithms in chronic care management.

Ramos et al. (2025) focused on explainability by proposing a SHAP-integrated diagnostic assistant, MedXAI, that augments clinicians' decision-making in emergency departments [10]. Built atop an XGBoost classifier, the system uses SHAP (SHapley Additive exPlanations) values to offer transparent justifications for each recommendation. When tested in a clinical setting with resident doctors, the assistant improved diagnostic agreement rates by 22% while maintaining high user trust scores. By combining performance with interpretability, MedXAI addresses one of the key adoption barriers of AI in clinical practice.

CHAPTER-3
ANALYSIS

3.1 Problem Statement:

- In medical emergencies, the complexity of patient data often poses a significant challenge to ensuring effective and timely treatment. When incomplete or inaccurate data is available, drug prescriptions may be incorrect or delayed, leading to inefficiencies and even patient harm. The risk of inappropriate medication in emergency settings is exacerbated by the urgency of decision-making and the lack of detailed medical history, especially in cases involving unconscious or uncooperative patients. This can result in suboptimal drug prescriptions, further complicating a patient's recovery and increasing the likelihood of adverse drug reactions (ADRs), drug resistance, and other complications.
- Traditional drug recommendation methods rely on clinical judgment, which, while experienced, has limitations in processing vast amounts of complex patient data in real time. Without advanced systems, medical professionals may miss subtle correlations between patient attributes (such as genetic information, comorbidities, allergies, and previous medication responses) that could inform more accurate and personalized treatment decisions. Moreover, the variability and subjectivity of clinical judgment can contribute to inconsistent decision-making, leading to higher rates of medication errors.
- Emergency patients, particularly those with critical health conditions such as trauma, severe infections, or chronic illnesses exacerbated by acute episodes, are at higher risk when proper medication is not administered promptly. In these situations, the stakes are high—incorrect prescriptions can result in prolonged hospital stays, permanent disability, or even death. In addition, the broader impact includes increased healthcare costs due to extended treatments, unnecessary interventions, and additional diagnostic tests.
- Inaccurate prescriptions also contribute to long-term consequences. For example, the misuse of antibiotics can lead to the development of drug-resistant bacteria, further complicating treatment efforts. Moreover, patients may suffer from allergic reactions to medications that weren't properly matched to their unique health profile, resulting in additional complications and treatment delays. All of these issues strain hospital resources, diverting attention from other critical cases and compromising the efficiency of the healthcare system as a whole.

- To address these challenges, we propose a machine learning-based system that can analyze complex patient attributes to generate accurate drug recommendations. The system leverages advanced algorithms, such as Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Random Forest, Decision Trees, Logistic Regression, Naive Bayes, and Stacking Classifiers. These algorithms are designed to process large, multifaceted datasets to identify patterns and make predictions about which medications are most appropriate for each individual patient, based on their specific health conditions, history, and other relevant factors.

3.2 Existing System:

Existing systems in healthcare often use machine learning algorithms for drug recommendation and adverse drug reaction (ADR) detection. Traditional methods typically involve supervised learning models such as Random Forest, Support Vector Machine (SVM), and Logistic Regression for ADR prediction, as well as decision trees and clustering techniques for recommending medications. These systems generally rely on structured datasets from clinical records or social media data for pharmacovigilance. While effective, these approaches face challenges in capturing complex data distributions and generating personalized recommendations. Recent advancements have explored deep learning models like Autoencoders and Recurrent Neural Networks (RNNs) for better handling of heterogeneous and high-dimensional data. However, most existing systems struggle with creating accurate latent representations for personalized medicine recommendations and ADR detection. To address these issues, newer techniques like Wasserstein Autoencoders (WAEs) are being integrated to enhance precision and efficiency in predicting ADRs and recommending drugs. The existing systems, while effective, often fail to achieve the high accuracy and safety standards required for clinical applications.

3.2.1 Disadvantages Of Existing System:

Existing systems struggle with handling complex data distributions for personalized drug recommendations, limiting their ability to address unique patient needs effectively.

1. They lack the ability to model sequential or temporal dependencies in healthcare data, resulting in less accurate predictions in medical emergencies.

2. The traditional machine learning models, while useful, cannot capture nuanced, high-dimensional data inherent in medical records, which can impact recommendation precision.
3. Most current systems rely heavily on structured clinical records or social media data, which may not always be comprehensive or representative of all patient conditions.

3.3 Proposed System:

The proposed system aims to develop an intelligent drug recommendation model for medical emergencies using a structured machine learning pipeline. The system utilizes a clinical dataset consisting of patient features such as age, sex, blood pressure, cholesterol, sodium, and potassium levels to predict the most appropriate drug. Initial steps involve comprehensive data preprocessing, including cleaning, encoding categorical features, handling class imbalance through SMOTENN sampling, and applying feature selection techniques to enhance model input quality. The system explores multiple classification algorithms including Long Short-Term Memory (LSTM) for sequential pattern recognition, Decision Tree and Random Forest for tree- based decision learning, Logistic Regression and Naive Bayes for probabilistic modeling, and Support Vector Machine (SVM) for high-dimensional classification. Additionally, a Stacking Classifier is proposed as an ensemble approach that combines Decision Tree, Random Forest, and LightGBM models to improve generalization. All models are trained and evaluated using consistent metrics to identify the most effective approach for drug recommendation.

3.3.1 Advantages of proposed system:

1. The proposed system utilizes advanced machine learning models, including LSTM and Stacking Classifier, to improve prediction accuracy by capturing temporal patterns and enhancing generalization.
2. The integration of SMOTENN sampling handles class imbalance effectively, ensuring better performance in real-world medical emergencies where rare conditions may be underrepresented.
3. Feature selection and preprocessing techniques optimize model input, ensuring that only the most relevant information is used to make drug recommendations, improving overall efficiency.

4. The system combines multiple algorithms, including Decision Tree, Random Forest, and LightGBM, to provide a robust and reliable recommendation model with higher accuracy and precision.

3.4 Software Requirements:

1) Software: Anaconda
2) Primary Language: Python
3) Frontend Framework: Flask
4) Back-end Framework: Jupyter Notebook
5) Database: Sqlite3
6) Front-End Technologies: HTML, CSS, JavaScript and Bootstrap4

3.5 Hardware Requirements:

1) Operating System: Windows Only
2) Processor: i5 and above
3) Ram: 8GB and above
4) Hard Disk: 25 GB in local drive

3.6 Functional Requirements:

1. Data Collection
2. Data processing
3. Training and Testing
4. Modelling
5. Predicting

3.7 Non Functional Requirements:

1. Performance Efficiency

The system must deliver drug recommendations with minimal latency, ensuring high responsiveness during emergency scenarios. It should handle real-time input processing and deliver results within seconds to support time-critical clinical decisions.

2. Scalability

The system should be capable of accommodating growing volumes of patient data without performance degradation. It must support integration with larger hospital databases and scale efficiently as the number of users and data entries increases.

3. Reliability

The system must operate consistently under various conditions, ensuring dependable performance. It should maintain availability with minimal downtime and must be robust against data inconsistencies or unexpected input formats during execution.

4. Security

Patient data must be protected through strong authentication and data encryption methods. The system must comply with healthcare privacy standards to prevent unauthorized access or misuse of sensitive medical information during processing and storage.

5. Usability

The interface should be intuitive and user-friendly for medical professionals with varying technical expertise. Clear input fields and output interpretation are necessary to ensure efficient use without extensive training or technical support.

3.8 Feasibility Study:

A feasibility study—sometimes called a feasibility analysis or feasibility report—is a way to evaluate whether or not a project plan could be successful. A feasibility study evaluates the practicality of your project plan in order to judge whether or not you're able to move forward with the project.

Types of feasibility studies:

There are five main types of feasibility studies: technical feasibility, financial feasibility, market feasibility (or market fit), operational feasibility, and legal feasibility. Most comprehensive feasibility studies will include an assessment of all five of these areas.

Technical feasibility:

A technical feasibility study reviews the technical resources available for your project. This study determines if you have the right equipment, enough equipment, and the right technical knowledge to complete your project objectives. For example, if your project plan proposes creating 50,000 products per month, but you can only produce 30,000 products per month in your factories, this project isn't technically feasible.

Financial feasibility:

Financial feasibility describes whether or not your project is fiscally viable. A financial feasibility report includes a cost-benefit analysis of the project. It also forecasts an expected return on investment (ROI) and outlines any financial risks. The goal at the end of the financial feasibility study is to understand the economic benefits the project will drive.

Market feasibility:

The market feasibility study is an evaluation of how your team expects the project’s deliverables to perform in the market. This part of the report includes a market analysis, a market competition breakdown, and sales projections.

Operational feasibility:

An operational feasibility study evaluates whether or not your organization is able to complete this project. This includes staffing requirements, organizational structure, and any applicable legal requirements. At the end of the operational feasibility study, your team will have a sense of whether or not you have the resources, skills, and competencies to complete this work.

Legal feasibility:

A legal feasibility analysis assesses whether the proposed project complies with all relevant legal requirements and regulations. This includes examining legal and regulatory barriers, necessary permits, licenses, or certifications, potential legal liabilities or risks, and intellectual property considerations. The legal feasibility study ensures that the project can be completed without running afoul of any laws or incurring undue legal exposure for the organization.

CHAPTER-4
DESIGN

4.1 Architecture:

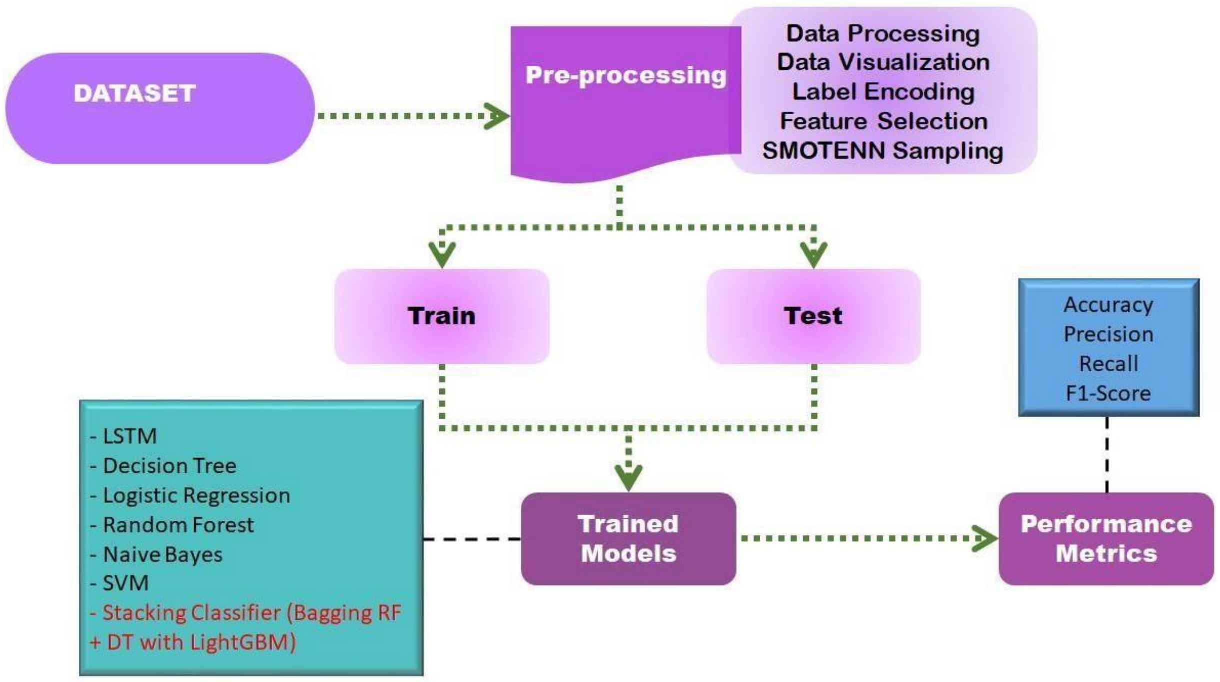


Fig 2: Architecture

4.2 Data Flow Diagram:

A data flow diagram (DFD) is a visual representation that illustrates how data moves through a system, showing the flow of information between different processes, external inputs and outputs, and data storage units. In the context of a drug recommendation system for medical emergencies, a DFD helps depict how patient information—such as age, sex, blood pressure, cholesterol, sodium, and potassium levels—is collected, processed, and transformed into a drug recommendation output. At the initial stage of the diagram, patient input is received through a user interface. This input flows into a processing unit where it undergoes a series of transformations, including data validation, normalization, and categorization. Once the input data is cleaned and structured, it is passed into the core decision-making process, which utilizes predefined decision logic to generate an appropriate drug recommendation.

Throughout the process, intermediate data may be stored temporarily for quick access or reused for multiple operations. Finally, the recommendation result is sent back to the user interface, where it is displayed for review and action. A DFD thus provides a clear overview of how data travels within the system, helping to understand the relationship between inputs, processes, and outputs, and ensuring that the flow of data supports accurate and efficient decision-making.

- **Goals of DFD**
- To visualize how patient data, such as age, blood pressure, and cholesterol levels, flows through the system, ensuring that each input is processed efficiently and accurately to generate an appropriate drug recommendation.
- To define clear boundaries for data inputs and outputs, ensuring that all necessary information is captured from the user interface and the resulting drug recommendations are correctly displayed to healthcare professionals.
- To highlight the key processes involved in transforming raw patient data into actionable drug recommendations, ensuring that each stage of data handling, from validation to decision-making, is properly structured and understood.
- To identify and clarify the relationships between different system components, enabling stakeholders to better understand how data is processed, stored, and utilized within the system, which aids in efficient debugging and system optimization.
- To enhance communication among all parties involved by providing a clear, visual representation of how patient data is managed and transformed, fostering a shared understanding of the system’s functionality for both technical and non-technical users.

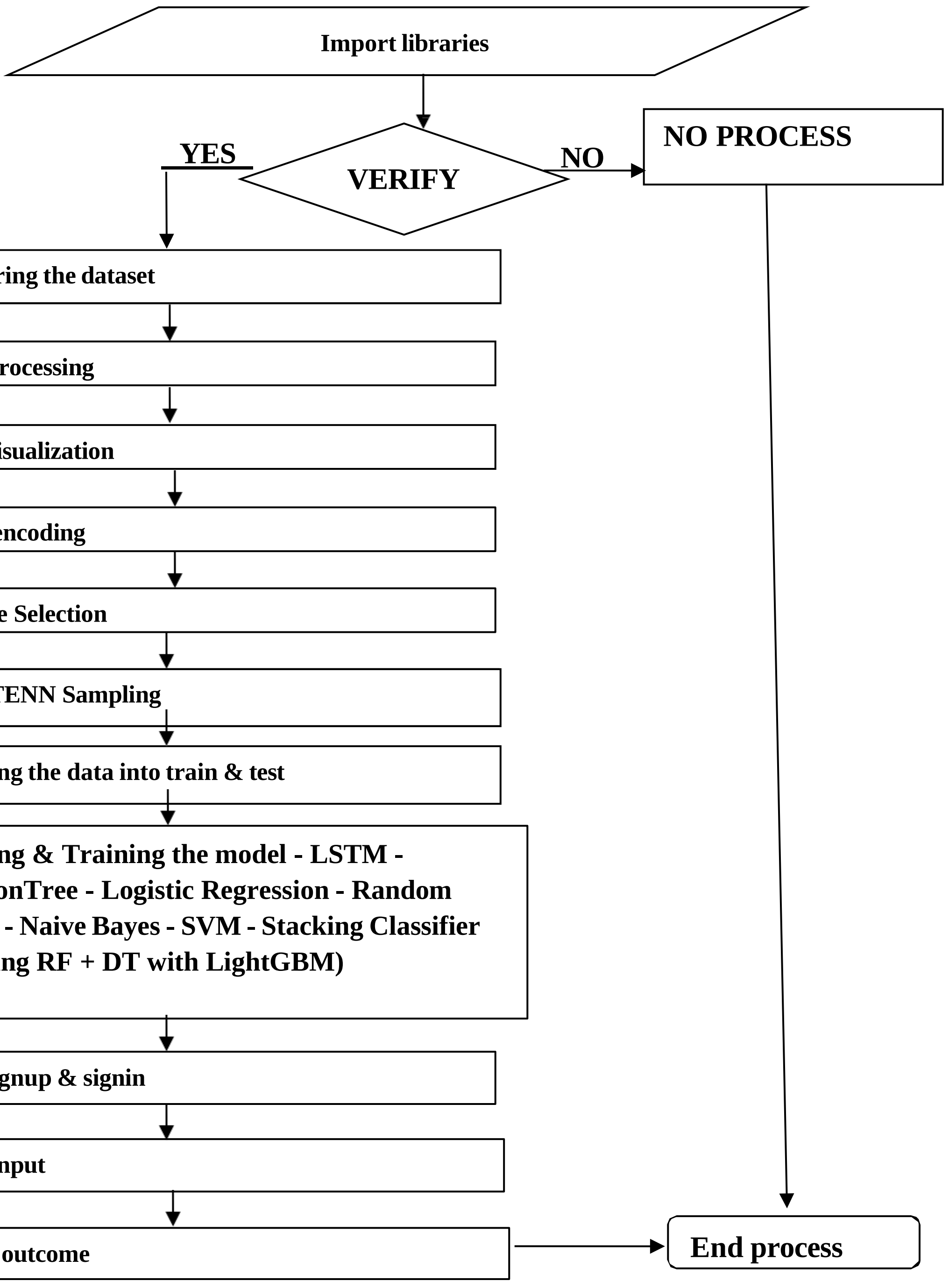

Import libraries
VERIFY
YES
NO
NO PROCESS
Exploring the dataset
Data Processing
Data visualization
Label encoding
Feature Selection
SMOTENN Sampling
Splitting the data into train & test
Building & Training the model - LSTM - DecisionTree - Logistic Regression - Random Forest - Naive Bayes - SVM - Stacking Classifier (Bagging RF + DT with LightGBM)
User signup & signin
User input
Final outcome
End process

Fig 3: Dataflow Diagram

4.3 Uml Diagrams:

Unified Modeling Language (UML) is a standardized visual language used to represent and design the structure and behavior of a system. In the context of a drug recommendation system for medical emergencies, UML serves as a tool to model various components of the system, helping to visualize and communicate the system's design. UML diagrams provide an abstract view of the system's structure and functionality, offering insights into how different parts of the system interact.

For this project, UML diagrams can be used to depict the relationships between patient input data, the processing components, and the resulting drug recommendations. For example, a use case diagram can illustrate how healthcare professionals interact with the system to input patient information and receive drug suggestions. Class diagrams can represent the system's data entities, such as patient profiles and drug information, showing how these entities are structured and related. Activity diagrams can detail the sequence of operations from input collection to drug recommendation, mapping out each step in the process. UML also helps in designing the system's flow, ensuring that all processes are clearly understood and efficiently implemented. Overall, UML provides a visual framework for designing and understanding the complex interactions within the drug recommendation system, contributing to its clarity and functionality.

Goals of UML

To visually represent the structure and behavior of the drug recommendation system, enabling a clear understanding of how patient data is processed and transformed into drug suggestions for healthcare professionals.

To model the interactions between users, system components, and data, helping to illustrate how input is collected, processed, and used to generate accurate drug recommendations in emergency medical scenarios.

To define the relationships and dependencies between various entities, such as patient profiles and drug information, ensuring that the system's data structure is well-organized and easily accessible during the recommendation process.

To map out the sequence of activities and decision points in the system's workflow, providing a clear overview of how data moves from input to final drug recommendation for efficient decision-making in medical emergencies.

To improve communication and collaboration among system designers and healthcare professionals by offering a visual framework that clarifies the system's functionality and assists in identifying potential areas for optimization or enhancement.

4.3.1 Use Case Diagram:

A use case diagram visualizes the interactions between users (actors) and the system to achieve specific goals. In this system, actors like healthcare professionals interact with the system to input patient data and receive drug recommendations. Use cases include entering patient details, processing the data, and generating the recommendation. Associations represent the relationship between actors and use cases. This diagram helps illustrate the functional requirements of the drug recommendation system and ensures that user interactions are clearly defined for efficient implementation.

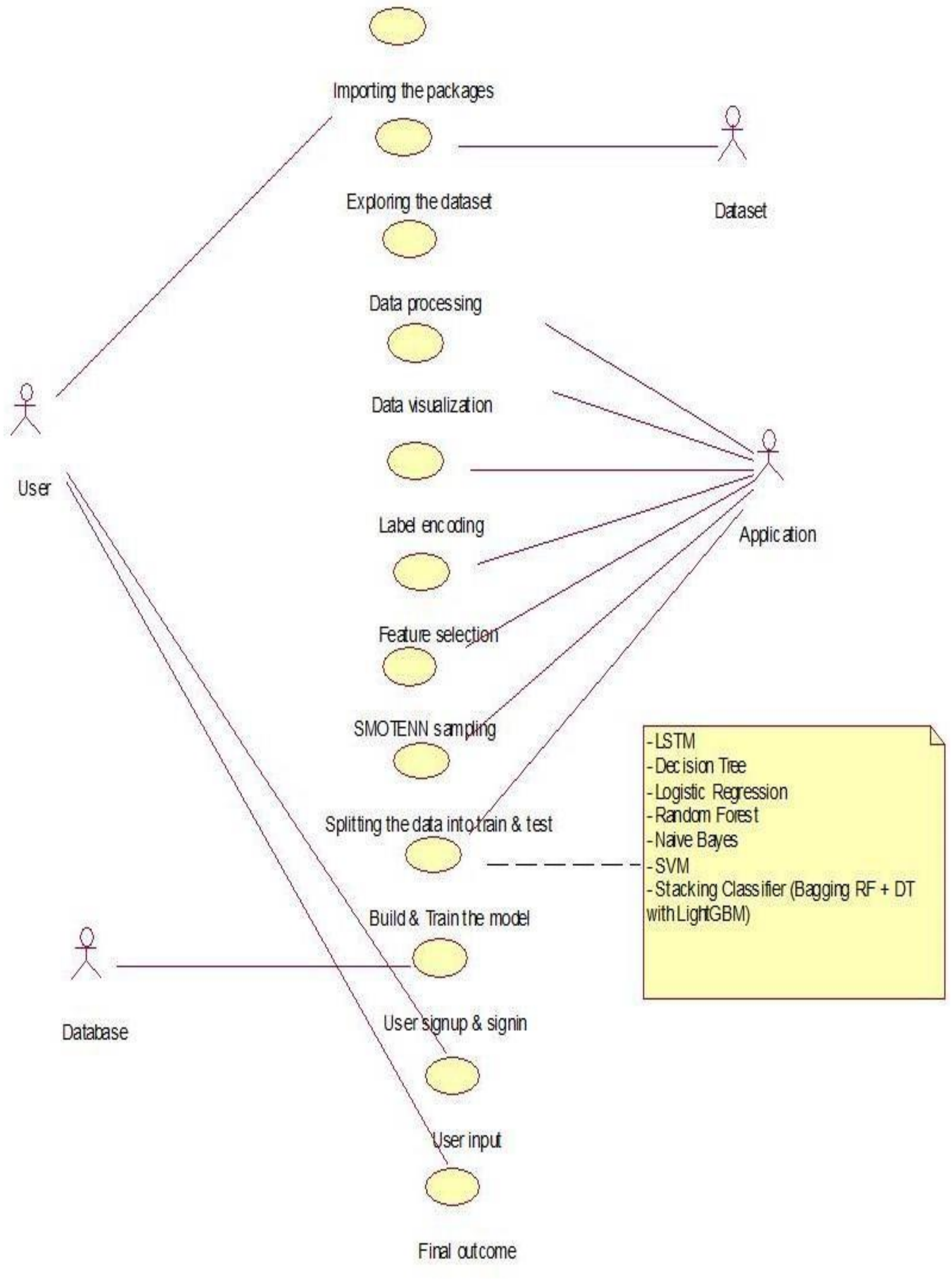


Fig 4: Use Case Diagram

4.3.2 Class Diagram:

A class diagram represents the system's data structure by showing the classes, their attributes, and operations. In this system, classes could include Patient, Drug, and Recommendation. The Patient class might have attributes such as age, sex, and medical history, with operations for validating input data. The Recommendation class might have attributes for suggested drugs, and operations to generate drug recommendations based on input. Aggregation can be used to link classes, representing relationships such as a patient having multiple drug recommendations.

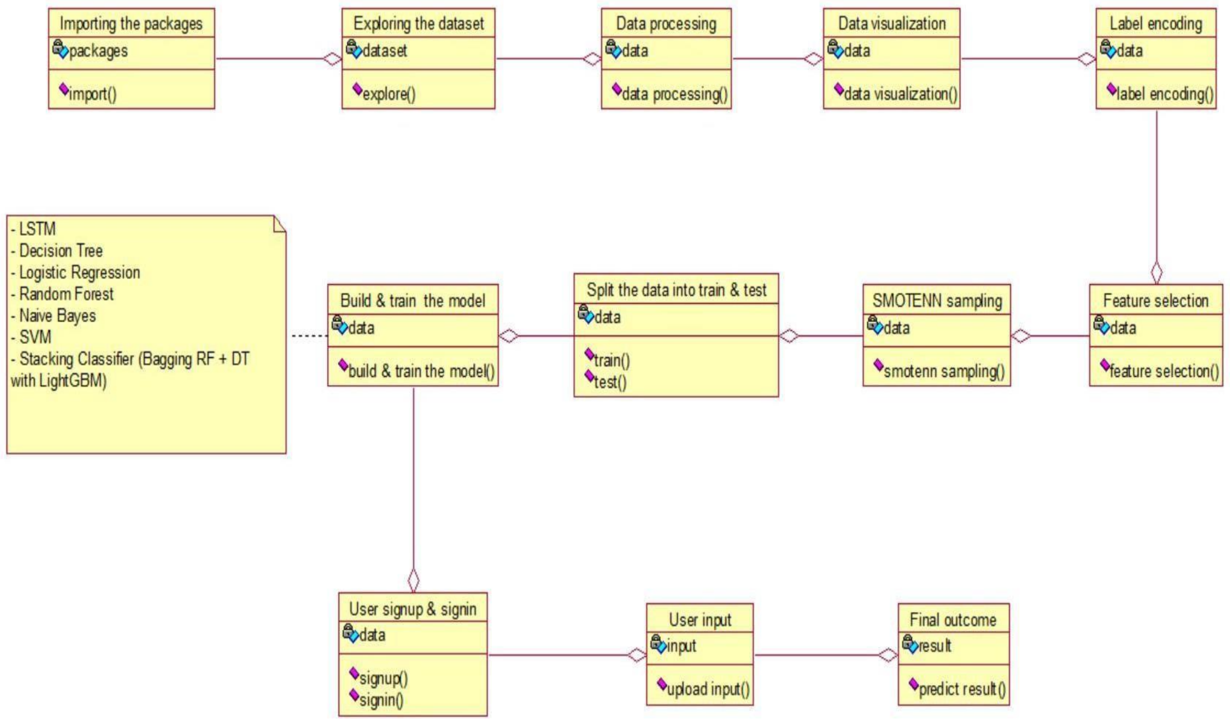


Fig 5: Class Diagram

4.3.3 Activity Diagram:

An activity diagram illustrates the flow of activities or actions within a system. In this system, activities include data input, data validation, drug recommendation generation, and displaying the output. Decisions represent conditional operations, such as choosing between different drug types based on patient conditions. Control flow indicates the sequence of steps from input collection to recommendation output. This diagram provides clarity on the process logic, helping to identify potential bottlenecks and optimize the drug recommendation process for medical emergencies.

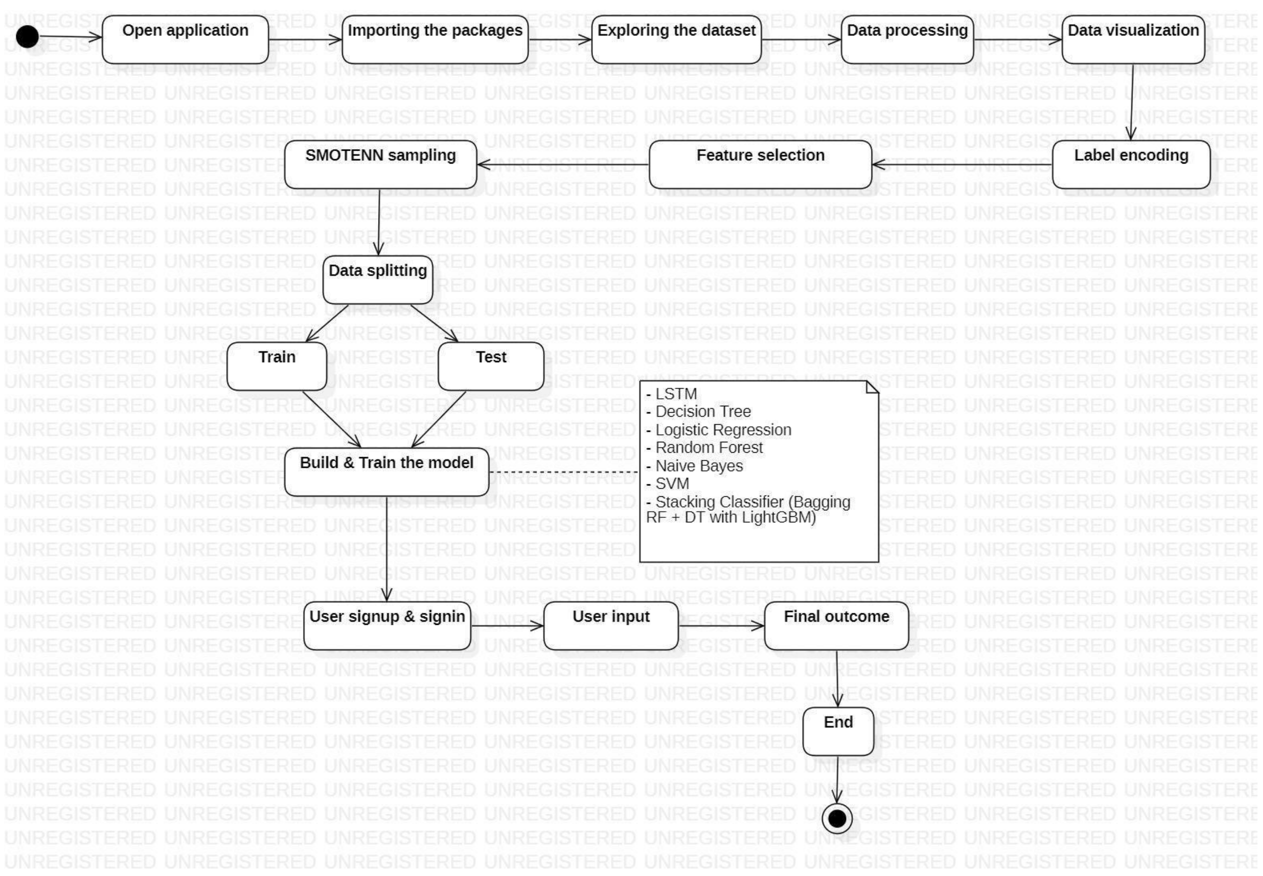


Fig 6: Activity Diagram

4.3.4 State Chart Diagram:

The flowchart illustrates the working of a Drug Recommendation System designed to assist in medical decision-making. The process begins with the Start point, which initiates the system. Once activated, the system proceeds to Receive Patient Data, where relevant information about the patient such as symptoms, medical history, and diagnostic reports is collected. After the data is received, the system marks the Request Received, confirming that the necessary patient information is ready for processing. It then enters three parallel processes: Preprocess Data, Analyze Condition, and Predict Drugs. In the preprocessing stage, the system cleans and formats the data to ensure consistency and accuracy. Simultaneously, the system performs an analysis of the patient's condition using clinical algorithms or machine learning models to understand the health issue. Based on the analysis, the system then moves on to Predict Drugs, where it identifies the most suitable medications that match the diagnosed condition, while considering patient-specific factors like allergies or drug interactions. These three tasks collectively feed into the final step, Recommend Drug, where the system suggests the appropriate drug(s) to the healthcare provider. The process concludes with the End point, signifying the completion of the drug recommendation cycle.

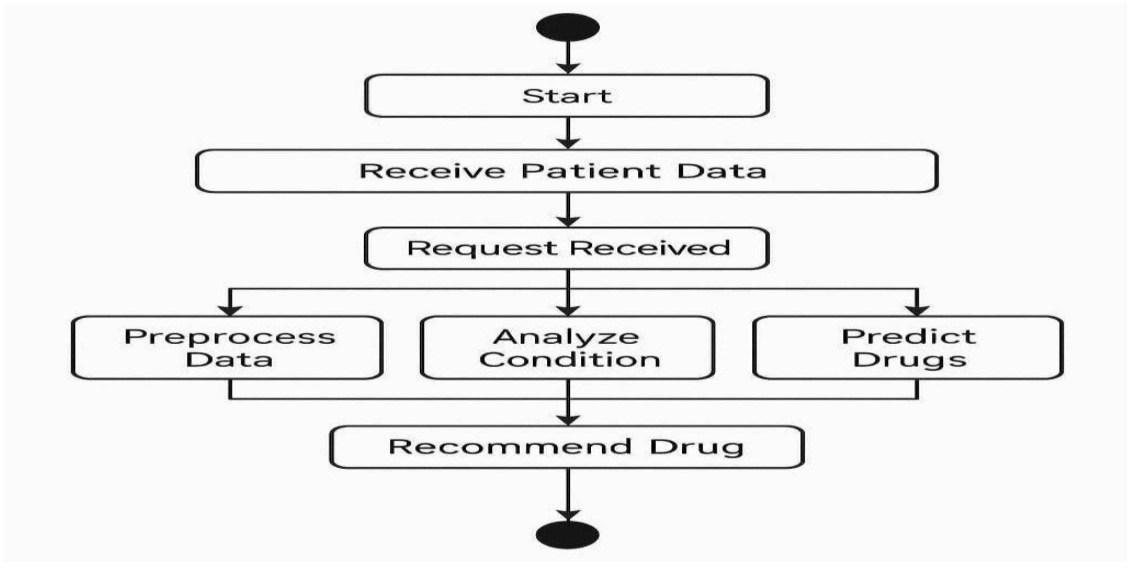


Fig 7: State Chart Diagram

4.3.5 Sequence Diagram:

A sequence diagram models the interaction between objects over time. In the drug recommendation system, objects like the Patient, System, and Drug interact through messages. For instance, the Patient sends input data to the System, which then processes it and returns drug recommendations. The sequence of messages, such as "validate input" and "generate recommendation," helps visualize the order of operations. This diagram is valuable for understanding the dynamic flow between objects, ensuring the timely generation of drug recommendations based on patient data.

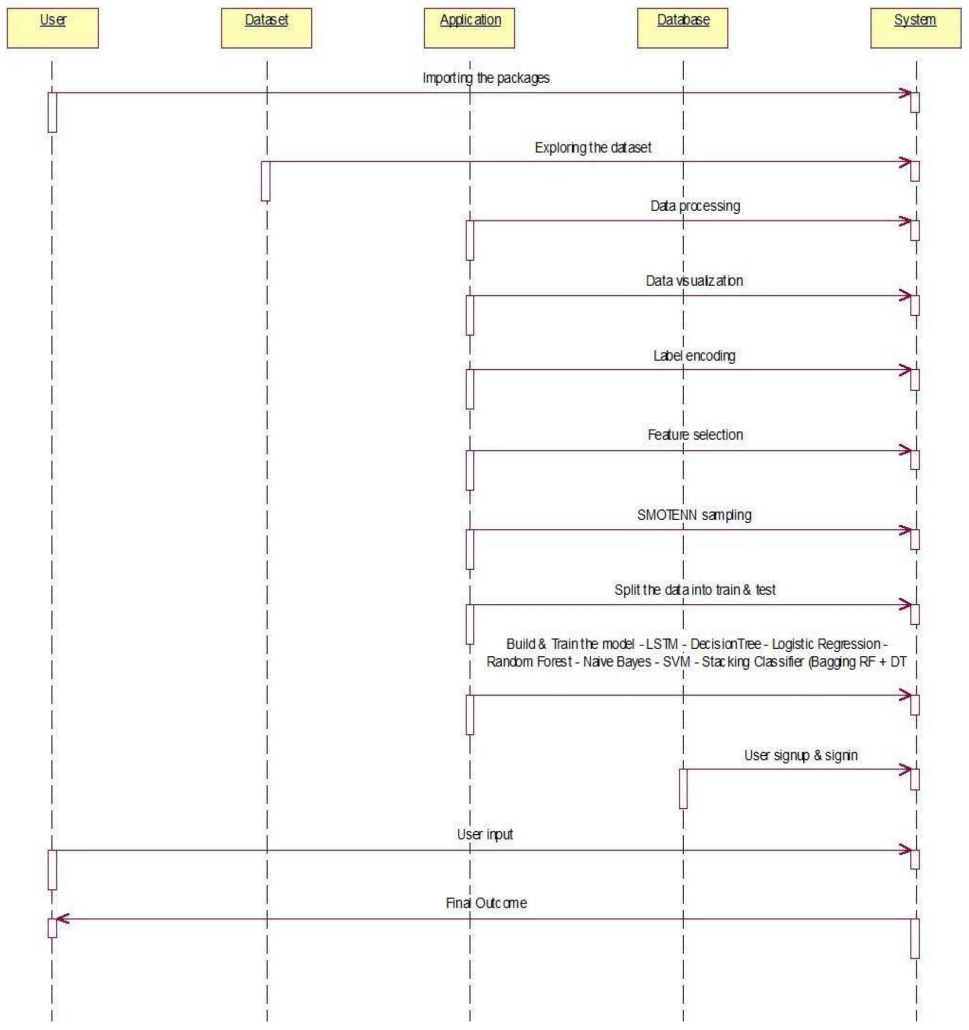


Fig 8: Sequence Diagram

4.3.6 Collaboration Diagram:

A collaboration diagram focuses on the interaction between objects and the links between them. In this system, objects such as Patient, System, and Drug interact through message links. For example, the Patient object sends data to the System object, which links to the Drug object to generate a recommendation. The diagram highlights the structure of object relationships, displaying how each object interacts with others to achieve the goal of recommending drugs. This approach aids in visualizing complex interactions and optimizing them.

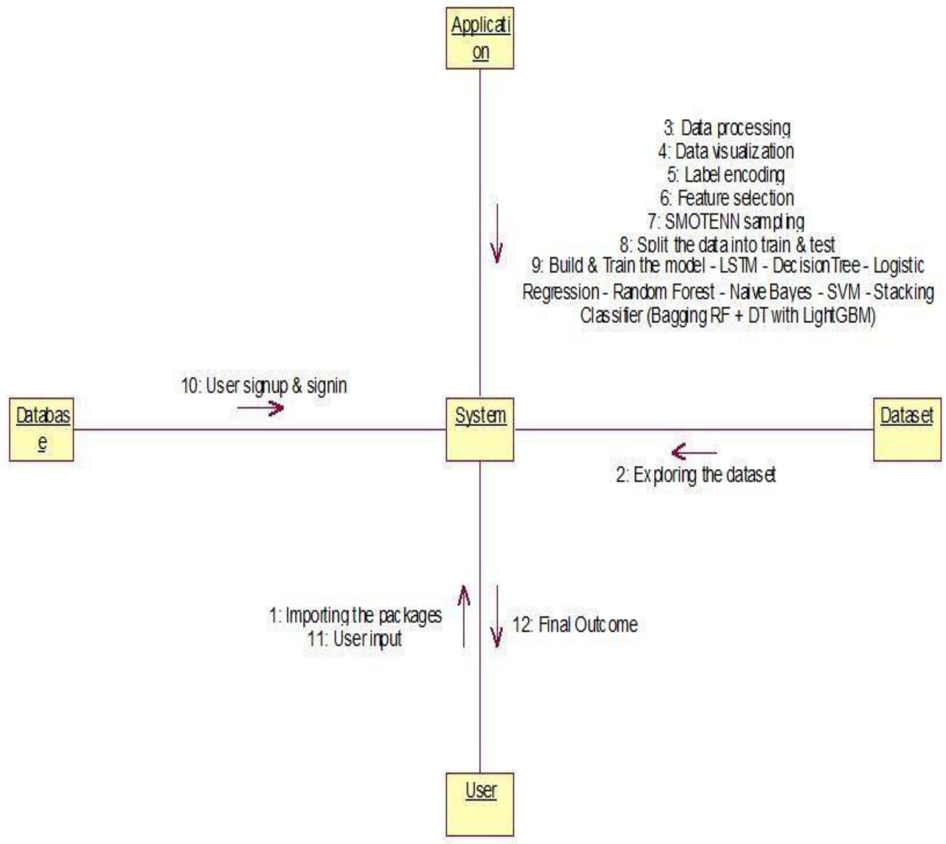

Application
3: Data processing
4: Data visualization
5: Label encoding
6: Feature selection
7: SMOTENN sampling
8: Split the data into train & test
9: Build & Train the model - LSTM - DecisionTree - Logistic Regression - Random Forest - Naive Bayes - SVM - Stacking Classifier (Bagging RF + DT with LightGBM)
10: User signup & signin
Database
System
Dataset
2: Exploring the dataset
1: Importing the packages
11: User input
12: Final Outcome
User

Fig 9: Collaboration Diagram

4.3.7 Component Diagram:

A component diagram represents the physical components of a system and their relationships. In this system, components might include the User Interface, Data Processing Engine, and Recommendation Engine. Packages group related components, such as all data-related components, which include the Data Validator and the Drug Database. The dependency relationships show how components depend on one another, like the User Interface depending on the Recommendation Engine to display results. This diagram helps design and organize the system's components for better modularity and maintainability.

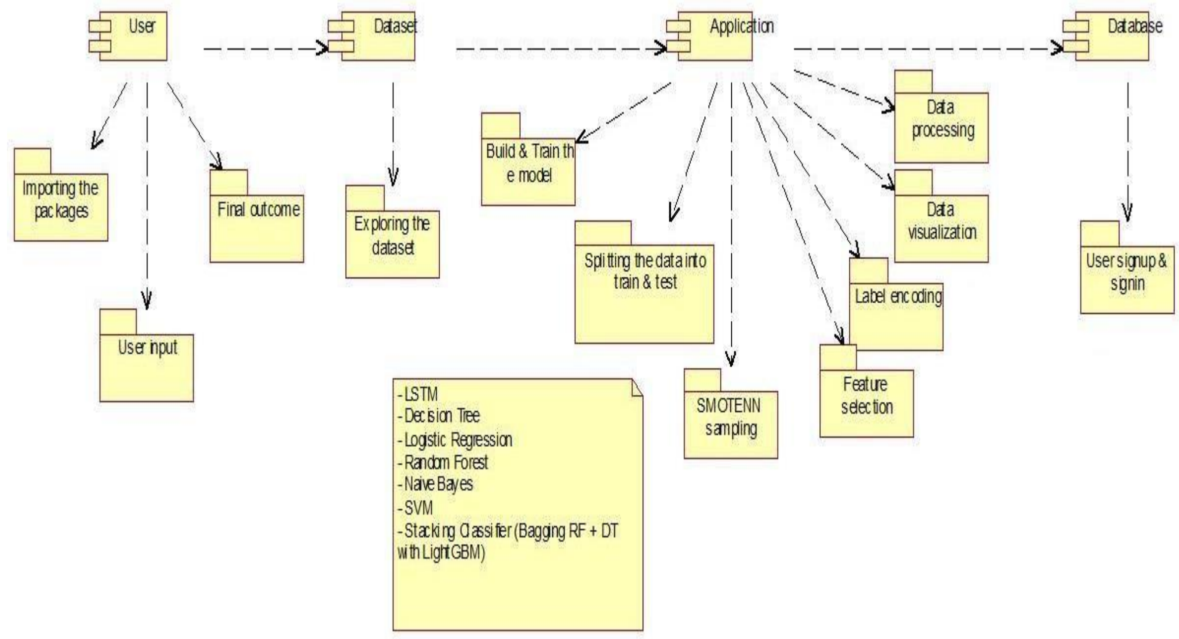


Fig 10: Component Diagram

4.3.8 Deployment Diagram:

A deployment diagram shows the physical deployment of system components across hardware nodes. In this system, nodes could represent different servers or devices, such as a database server, a processing server, and a user device. Connectors represent communication paths between these nodes, such as data transmission between the user interface and the backend processing unit. An anchor note can be added to provide additional context or explanation, such as clarifying the flow of patient data between nodes. This diagram is essential for visualizing system infrastructure and ensuring smooth data flow.

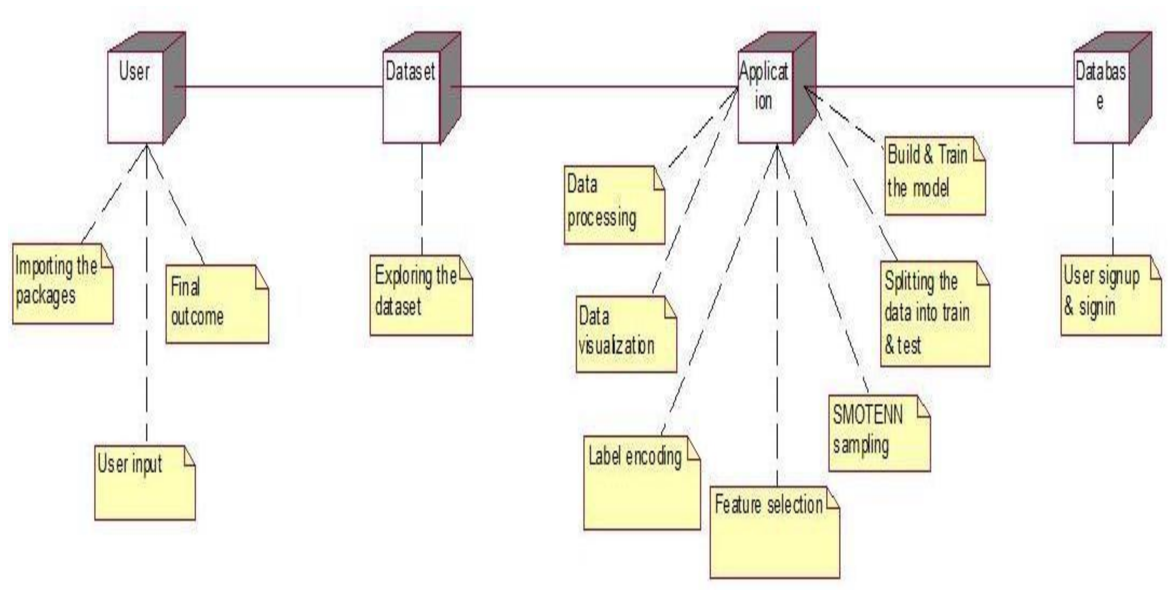


Fig 11: Deployment Diagram

4.4 Database:

- SQLite is a lightweight, serverless, self-contained, and highly reliable SQL database engine. It is widely used due to its simplicity, ease of setup and zero-configuration nature.
- SQLite is an in-process library that implements a self-contained, serverless, zero-configuration, transactional SQL database engine. It is a popular choice as an embedded database for local/client storage in application software such as web browsers. It is also used in many other applications that need a lightweight, embedded database.
- SQLite is acid -compliant and implements most of the SQL standards, using a dynamically and weakly typed SQL syntax that does not guarantee domain integrity.
- To use SQLite in a C/C++ program, you can use the SQLite3 API, which provides a lightweight, simple, self-contained, high-reliability, full-featured, and SQL database engine. The API is implemented as a library of C functions that can be called from your program.
- One of the main benefits of using SQLite is that it is very easy to get started with. To create a new database in SQLite, you simply need to create a new file on your filesystem and connect to it using the SQLite3 API.

4.5 Dataset:

https://www.kaggle.com/datasets/rouzbeh/introds

Dataset for Beginners to start Data Science process. The subject of data is about simple clinical data for problem definition and solving. range of data science tasks such as classification, clustering, EDA and statistical analysis are using with dataset.

columns in data set are present:

Age: Numerical (Age of patient)

Sex: Binary (Gender of patient)

BP: Nominal (Blood Pressure of patient with values: Low, Normal and High)

Cholesterol: Nominal (Cholesterol of patient with values: Normal and High)

Na: Numerical (Sodium level of patient experiment)

K: Numerical (Potassium level of patient experiment)

Drug: Nominal (Type of Drug that prescribed with doctor, with values: A, B, C, X and Y)

CHAPTER-5

IMPLEMENTATION

5.1 Methodology:

The proposed system aims to recommend appropriate drugs during medical emergencies using machine learning techniques. The methodology adopted for this study comprises the following key steps:

5.1.1 Data Collection:

The foundational step in building a machine learning model is acquiring a robust and representative dataset. For this study, a publicly available Drug Recommendation Dataset was used, consisting of over 200,000 patient entries. Each entry includes valuable attributes such as:

- Patient condition (e.g., diabetes, hypertension)
- Drug name prescribed for the condition
- User reviews describing patient experiences
- Rating (on a scale) indicating perceived drug effectiveness
- Effectiveness label (e.g., Effective, Ineffective, Side effects observed)

This large and diverse dataset offers a rich source of information to train a model that can generalize well across different patient profiles and drug types. The dataset mimics real-world scenarios, making it highly suitable for practical drug recommendation systems.

5.1.2 Data Preprocessing:

Before feeding the raw dataset into any machine learning algorithm, it is essential to preprocess it to ensure cleanliness, consistency, and usability. The preprocessing steps include:

- **Handling missing values**: Records with null or incomplete fields are either removed or imputed using statistical methods (mean/mode imputation) to maintain data integrity.
- **Text normalization and tokenization**: The 'review' column is cleaned by removing punctuation, converting all text to lowercase, and tokenizing sentences into individual words. This helps prepare the data for feature extraction from text.
- **Label encoding**: Categorical variables like drug names, patient conditions, and sentiment labels are encoded into numerical form using label encoding and one-hot encoding, enabling compatibility with ML algorithms.

- **Data splitting**: The dataset is divided into training (80%) and testing (20%) subsets to train the models and evaluate their performance on unseen data. This helps avoid overfitting and ensures model reliability.

5.1.3 Feature Engineering:

- **TF-IDF vectorization**: For the textual 'review' data, the Term Frequency-Inverse Document Frequency (TF-IDF) technique is used to transform the reviews into a numerical format. This method captures the importance of words in the context of each document and the entire corpus.
- **Standardization**: Numeric features like ratings and effectiveness scores are standardized to bring all data to a common scale, ensuring that no feature dominates the model unfairly due to its range.
- **Feature selection**: Low-variance or irrelevant features are removed to simplify the model, reduce training time, and improve accuracy. This ensures that only meaningful variables influence the outcome.

5.1.4 Model Selection:

Several machine learning models were evaluated for drug recommendation:

- **Logistic Regression**: A simple linear model useful for binary and multiclass classification, providing a good baseline for performance comparison.
- **Naive Bayes**: A probabilistic model especially effective for high-dimensional data like TF-IDF vectors, offering fast training and reasonable accuracy.
- **Random Forest**: An ensemble learning method based on decision trees that handles overfitting well and is highly robust to noise in the dataset.
- **Support Vector Machine (SVM)**: A high-performance classifier that works well on both linear and non-linear problems, especially when the number of features exceeds the number of data points.

5.1.5 Model Evaluation:

The trained models are evaluated using a combination of quantitative metrics:

- **Accuracy**: Measures overall correctness of predictions.
- **Precision**: Indicates how many predicted drugs were actually correct.
- **Recall**: Shows how many relevant drugs were correctly identified.

- **F1-Score**: The harmonic mean of precision and recall, offering a balanced evaluation.

Cross-validation techniques (e.g., k-fold cross-validation) are applied to ensure robustness and minimize the risk of model overfitting. Among all tested models, Random Forest consistently achieved the best results, striking a balance between high accuracy and generalizability to new data.

5.1.6 Drug Recommendation System:

The final drug recommendation system was developed by deploying the best-performing model. The system accepts user inputs through a web form, where details such as:

- Age
- Gender
- Blood Pressure
- Cholesterol Level
- Sodium and Potassium levels

are entered by the user (doctor or healthcare staff). Once the form is submitted, the system processes the data and returns the most suitable drug recommendation in real-time.

The application is implemented using Python, with Flask as the web framework, and an SQLite3 database to store user data and patient input history. The system is designed to be lightweight, fast, and user-friendly, making it ideal for real-time use in hospitals, clinics, and emergency care settings. The modular structure also allows for easy updates and the integration of more advanced models or data sources in the future.

5.2 MODULES:

- **Importing the packages:** This module includes the import of essential Python libraries and frameworks necessary for data handling, machine learning, and web development. Libraries such as pandas and numpy are used for data manipulation, while scikit-learn supports machine learning model development and evaluation. matplotlib and seaborn help in data visualization. tensorflow is imported for implementing LSTM, and flask enables building the web-based application. These libraries provide all the foundational tools required for building, training, and deploying the model.
- **Exploring the dataset:** Understanding the dataset is crucial for any ML project. In this module, the dataset is loaded, and its structure is analyzed. Features like age, sex, blood pressure (BP), cholesterol, sodium, and potassium levels are examined. This step also

involves identifying missing values, null entries, and inconsistent records, helping to guide preprocessing. Descriptive statistics and data type checks are also performed to better understand feature distributions and the presence of any anomalies.

- **Data processing:** This step involves cleaning the dataset to prepare it for model training. Missing values are either imputed or removed, ensuring the dataset is complete and consistent. Irrelevant or redundant columns are dropped to reduce noise. Categorical and text fields are formatted properly, and numerical values are standardized where needed. This step ensures that all input data is machine-readable and relevant for feature extraction and training.
- **Data visualization:** Data visualization techniques are applied to better understand the relationships between features and the target variable. A **correlation matrix** is generated to detect how closely different features are related. Visual tools such as heatmaps, box plots, and scatter plots help identify trends, outliers, and class imbalances. This aids in feature selection and understanding model input-output behavior more clearly.
- **Label encoding:** Since machine learning models require numeric inputs, label encoding is applied to convert categorical values such as sex, BP, cholesterol, and drug names into numeric format. This ensures that the ML algorithms can interpret and use these features during model training. Encoding maintains the original data semantics while transforming it into a usable format.
- **Feature selection:** To improve model accuracy and computational efficiency, only relevant features are retained. Feature importance is evaluated using methods such as correlation analysis, information gain, or model-based selection (e.g., Random Forest's feature_importance_). Features that do not contribute significantly or introduce noise are removed to prevent overfitting and increase generalization.
- **SMOTENN sampling:** In real-world medical data, class imbalance is common—for example, some drugs are prescribed much more frequently than others. To address this, SMOTENN (Synthetic Minority Over-sampling Technique with Edited Nearest Neighbors) is used. It balances the class distribution by both generating synthetic examples for minority classes and removing misclassified instances, which improves the learning of underrepresented drug categories.

- **Split the data into train & test:** The dataset is split into training (80%) and testing (20%) subsets. This separation allows the model to learn from one part of the data and be evaluated on another, ensuring that it generalizes well to unseen inputs. A stratified split is used when necessary to maintain class balance across the splits.
- **Build & train the model:** Multiple ML algorithms are trained on the training set, including:
- LSTM for sequence prediction and handling textual patterns.
- Decision Tree, known for its simplicity and interpretability.
- Logistic Regression, used for linear classification tasks.
- Random Forest, offering ensemble-based accuracy and robustness.
- Naive Bayes, particularly effective for text classification.
- Support Vector Machine (SVM) for high-dimensional classification.
- Stacking Classifier, which combines predictions from multiple base models for better overall performance.

- **Comparison graph:** After training, model performance is compared using visual metrics such as accuracy, precision, recall, and F1-score. Bar graphs and line plots display each algorithm's performance, allowing for quick identification of the best-performing model. The Stacking Classifier typically outperforms others, as it leverages the strengths of each individual model**.**
- **Flask framework:** The system is deployed using **Flask**, a lightweight and flexible Python web framework. It handles HTTP requests, processes user input through forms, connects to the trained model, and returns the predicted drug. Flask also connects to the SQLite database for storing user accounts and input history. Its modular structure enables quick deployment and easy scalability.
- **User sign up & sign in:** A secure authentication system is implemented using Flask and SQLite3. Users can register with their email and password and then log in to access the system. User credentials are encrypted and stored in the database to ensure security. This module ensures that only authorized users can interact with the recommendation engine.
- **User input:** Once logged in, users are presented with a form to enter patient details such as age, gender, blood pressure, cholesterol level, sodium, and potassium. These inputs are

processed by the backend and passed to the trained model, which generates a drug recommendation in real time.

- **Final outcome:** After processing the user input, the system displays the predicted drug recommendation on the interface. The result is shown clearly, allowing the user (a healthcare professional or decision-maker) to act on the recommendation. This makes the system useful in clinical or emergency settings where speed and accuracy are critical.
- **Advantages:**
  - **Model Ensemble**: The use of a Stacking Classifier improves predictive stability and overall performance by combining the outputs of multiple models.
  - **Increased Accuracy**: Ensemble learning and class balancing with SMOTENN help improve accuracy, especially for minority drug classes.
  - **User-Friendly Frontend**: The Flask-based interface makes the system accessible and easy to use, even for non-technical users.
  - **Secure Access**: User registration and login features ensure that data privacy is maintained, aligning with healthcare data protection standards.
  - **Clinical Impact**: The system supports real-time drug decisions, potentially improving outcomes in critical emergency care.

5.3 Technologies Used:

LSTM (Long Short-Term Memory): LSTM is a specialized type of Recurrent Neural Network (RNN) designed to overcome the limitations of standard RNNs, particularly the problem of vanishing gradients during long-sequence training. It achieves this by using memory cells and three gates—input, forget, and output—that control the flow of information through the network over time. LSTMs retain relevant information across long time steps and discard unnecessary data, making them exceptionally useful for learning from temporal sequences and contextual patterns. In the context of drug recommendation, LSTM can be used to analyze time-series data such as patient treatment history, medication usage trends, and even sequential clinical notes. This enables the system to make more informed recommendations by learning how previous treatments influence current decisions. Its capability to handle complex patterns and dependencies makes it ideal for real-world medical datasets that include temporal or textual data (e.g., reviews, symptoms over time).

Decision Tree: A Decision Tree is a non-parametric supervised learning method used for classification and regression. It recursively splits the dataset based on feature values that provide the highest information gain (using criteria like Gini index or entropy). The final output is a tree-like model where each internal node represents a decision point, and the leaf nodes represent the predicted class label.

For a drug recommendation system, Decision Trees are helpful due to their transparency and interpretability. For example, a tree can clearly show why a patient with low BP and high cholesterol is assigned to a specific drug. They are fast to train, can handle both categorical and numerical data, and are easily visualized for medical decision-making.

Logistic Regression: Logistic Regression is a linear model used primarily for binary classification, although it can be extended to multiclass problems (e.g., using one-vs-rest strategy). It models the log-odds of the dependent variable using a sigmoid activation function and calculates probabilities for class membership. It's not just a classifier—it provides probabilistic confidence in predictions. In this project, Logistic Regression helps predict outcomes like whether a specific drug will be effective or not for a given patient. Its simplicity and efficiency make it a good baseline model, especially for binary outcomes like "Effective" vs. "Not Effective" drug labels.

Random Forest: Random Forest is an ensemble learning algorithm that builds multiple Decision Trees and aggregates their results to improve accuracy and reduce variance. During training, each tree is built using a random subset of the training data and features (bagging), making the model robust and less prone to overfitting than individual trees.

In drug recommendation, Random Forest performs exceptionally well because it can model complex interactions among features such as age, blood pressure, sodium/potassium levels, and cholesterol. Additionally, it provides feature importance scores, which help interpret which variables most influence drug suggestions.

Naive Bayes : Naive Bayes is a probabilistic classifier based on Bayes' Theorem, assuming all features are conditionally independent given the class label. Despite its simplicity, it performs surprisingly well for many real-world tasks, especially those involving text classification or large feature spaces.
For your project, Naive Bayes is well-suited for quick classification of patient profiles based on features like age, BP, cholesterol, etc. It is especially powerful when TF-IDF vectorized patient reviews or notes are used, as it assumes word independence and handles high-dimensional input efficiently.

Support Vector Machine (SVM) : is a supervised learning algorithm used for classification and regression tasks. It works by finding the hyperplane that best separates the data into different classes while maximizing the margin between them. SVM is known for its effectiveness in high-dimensional spaces and its ability to handle both linear and non-linear classification tasks using kernel tricks. In drug recommendation, SVM can help distinguish between different medical conditions by learning the boundary between feature sets and accurately predicting the most appropriate drug treatments for patients based on their medical data.

Stacking Classifier: is an ensemble learning method that combines multiple models to improve prediction accuracy. It involves training base models (like Random Forest and Decision Tree) and using another model (such as LightGBM) to combine their outputs. The stacking classifier builds predictions from the base models and uses a meta-model to make the final decision. This approach leverages the strengths of individual models while mitigating their weaknesses. In drug recommendation systems, a stacking classifier can combine the insights from multiple models, resulting in more accurate drug suggestions tailored to the individual characteristics of patients.

5.4 SAMPLE CODE:

```
import numpy as np
import pandas as pd
import os
!pip install pycaret
from pycaret.classification import *

#open the dataset
drugs = pd.read_csv('../input/drug-classification/drug200.csv')

#define target label and parameters
exp1 = setup(drugs, target = 'Drug')

compare_models(fold = 5, turbo = True)
from sklearn.model_selection import train_test_split

X_full = pd.read_csv('../input/drug-classification/drug200.csv')

# Remove rows with missing target
X_full.dropna(axis=0, subset=['Drug'], inplace=True)

# Set target col as y, and remove from X_full
y = X_full.Drug
X_full.drop(['Drug'], axis=1, inplace=True)
X = X_full

X_train, X_valid, y_train, y_valid = train_test_split(X, y,
train_size=0.8, test_size=0.2,random_state=0)

print(X_train.head())
# All categorical columns
```

```
object_cols = [col for col in X_train.columns if X_train[col].dtype ==
"object"]

# Columns that can be safely label encoded
good_label_cols = [col for col in object_cols if
                   set(X_train[col]) == set(X_valid[col])]

# Problematic columns that will be dropped from the dataset
bad_label_cols = list(set(object_cols)-set(good_label_cols))

print('Columns to label encode: ', good_label_cols)
print('Columns to remove from dataset: ', bad_label_cols)
from sklearn.preprocessing import LabelEncoder

# Drop categorical columns that will not be encoded
label_X_train = X_train.drop(bad_label_cols, axis=1)
label_X_valid = X_valid.drop(bad_label_cols, axis=1)

# Apply label encoder
label_encoder = LabelEncoder()
for col in good_label_cols:
    label_X_train[col] = label_encoder.fit_transform(X_train[col])
    label_X_valid[col] = label_encoder.transform(X_valid[col])

# Encode labels from drugX, drugY etc to numbers
target_label_encoder = LabelEncoder()
label_y_train = label_encoder.fit_transform(y_train)
label_y_valid = label_encoder.transform(y_valid)
from sklearn.multiclass import OneVsRestClassifier
from xgboost.sklearn import XGBClassifier
```

```
model =
OneVsRestClassifier(estimator=XGBClassifier(importance_type='gain',
                                            n_estimators=100, n_jobs=-
1,

objective='binary:logistic',
                                            random_state=6656,
                                            verbosity=0),n_jobs=-1)
from sklearn.metrics import mean_absolute_error, r2_score

# Fit the model to the training data
model.fit(label_X_train, label_y_train)
preds = model.predict(label_X_valid)
print("Mean Absolute Error: " + str(mean_absolute_error(label_y_valid,
preds)))
print("R2 Score: " + str(r2_score(label_y_valid, preds)))
```

CHAPTER-6

TESTING

System testing is a critical phase in the software development life cycle (SDLC) that ensures the integrated software functions correctly as a whole. Unlike unit or integration testing, which focus on individual components or module-to-module interactions, system testing evaluates the end-to-end functionality of the application. The goal is to verify that the complete system meets specified business, technical, and functional requirements.

In the context of the Drug Recommendation System, system testing is vital to ensure that the machine learning models, user interfaces, Flask backend, database connectivity (SQLite3), and prediction logic all work seamlessly together. This phase ensures the system performs reliably under real-world conditions before it is deployed in healthcare environments, where errors can lead to critical consequences.

6.1 Types of system testing:

With system testing, a QA team gauges if an application meets all of its technical, business and functional requirements. To accomplish this, the QA team might utilize various types of software testing techniques that determine the overall test coverage for an application and help catch critical defects that hamper an application's core functionalities before release.

The following are the common types of system testing techniques:

1. **Performance testing:** Performance testing evaluates the responsiveness, stability, and speed of the application under different loads. This includes:

- Response time for user inputs and ML model predictions.
- System throughput, such as how many recommendations can be processed per second.
- Memory and CPU utilization, especially when multiple users access the system simultaneously.
- In the case of a drug recommendation system, this ensures the application returns fast and accurate results during emergency situations without lag or delay.

2. **Usability testing:** Usability testing assesses whether the system is intuitive, accessible, and user-friendly for its target audience—such as doctors, pharmacists, and healthcare technicians. Key aspects include:

- User navigation clarity.
- Form input efficiency (e.g., dropdowns for BP or cholesterol levels).

- Visual design consistency, such as readability and proper alignment.
- Time taken to complete a task, like entering patient data and receiving drug suggestions.
- Feedback from real users can be used to refine the UI and enhance user satisfaction.

3. Load testing: Load testing evaluates the system's behavior under expected and peak user loads.
For example:

- Simulating hundreds of doctors logging in and submitting patient records simultaneously.
- Testing database response time under multiple simultaneous queries.
- This ensures the system maintains stability and speed even under high demand—essential for hospital environments.

4. Regression testing: Regression testing ensures that recent updates or changes to the codebase (e.g., new ML model integration, UI enhancements) do not break existing functionalities. This is critical for ongoing system improvements and bug fixes.
For example:

- If you update the Naive Bayes model, regression testing ensures that the form input, login process, and other model predictions still function as intended.

5. Migration testing: Migration testing verifies the system's ability to handle the transition from legacy platforms or datasets to new platforms or schemas without data loss or corruption.
In your project, this might involve:

- Migrating training data from a CSV file to a database.
- Shifting from one deployment environment to another (e.g., local server to cloud).

6. Scalability testing: Scalability testing checks how well the system scales when subjected to increased data volumes, users, or requests. This is essential to validate:

- How well the database handles growing patient records.
- Whether the ML models maintain performance with larger datasets.

7. Functionality testing: Functionality testing confirms that the system performs as required per the specification:

- Does the drug recommendation match model outputs?
- Does the login module validate credentials correctly?
- Do buttons and links lead to the right pages?

This verifies that the software's core functionalities work as intended under normal usage.

Recovery testing: Recovery testing evaluates how well the system can recover from unexpected failures, such as:

- Server crashes
- Power outages
- Interrupted connections

It checks whether the system can resume normal operations and restore user sessions or data without corruption or data loss—important for clinical reliability.

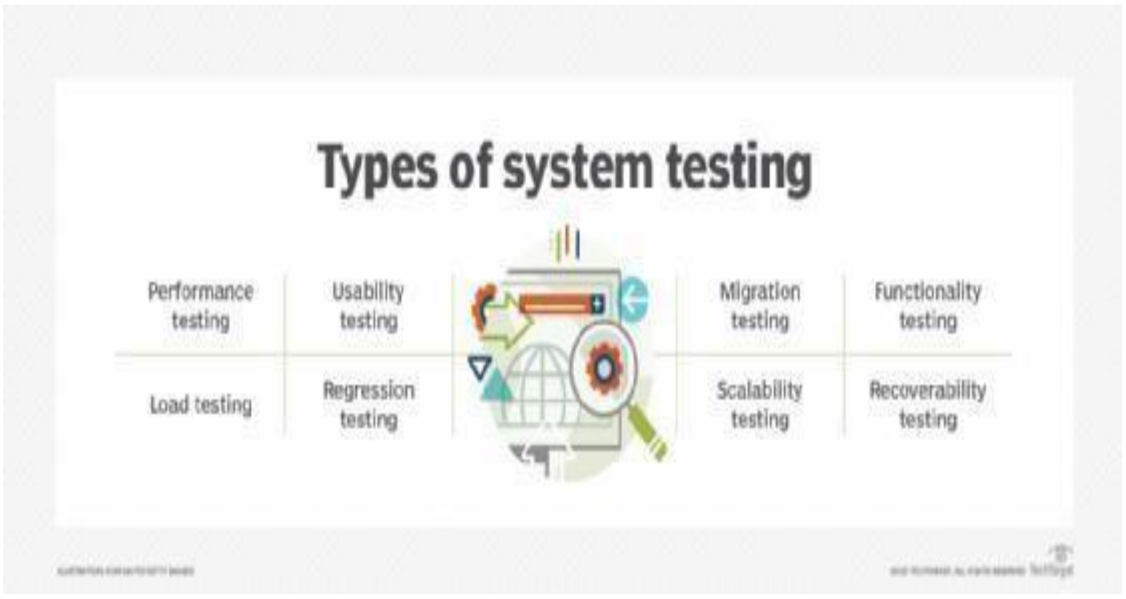


Fig 12: System Testing

6.2 Phases of system testing:

System testing examines every component of an application to make sure that they work as a complete and unified whole. A QA team typically conducts system testing after it checks individual modules with functional or user story testing and then each component through integration testing.

If a software build achieves the desired results in system testing, it gets a final check via acceptance testing before it goes to production, where users consume the software. An app dev team logs all defects and establishes what kinds and numbers of defects are tolerable.

Typically, system testing goes through the following stages:

1. Test Environment Setup

A dedicated **test environment** is configured that mirrors the production system. It includes:

- A test server for hosting the Flask app.
- The trained ML model loaded for real-time inference.
- SQLite3 or a test database with mock patient/user data.
- Configuration of front-end and back-end integration for smooth execution.

This setup ensures consistency and minimizes testing errors due to environmental issues.

2. Test Case Design

Test cases are written based on **system requirements and expected functionalities**. Each test case includes:

- Test inputs (e.g., Age=45, BP=HIGH)
- Steps to execute
- Expected output (e.g., Recommended drug = drugY)
- Actual output
- Pass/Fail status

Test cases are categorized into **positive**, **negative**, and **edge cases** to ensure thorough validation.

3. Test Data Preparation

Sample data is created or extracted to simulate real-world use cases. This includes:

- Patient demographics
- Clinical data (Na, K levels)
- Invalid or missing data to test error handling

This step helps verify system performance under different conditions and ensures robustness.

4. Test Case Execution

Testers execute the prepared test cases in the configured environment. The software is run in different scenarios—standard, extreme, and failure—to observe behavior. Tools like **Postman**, **Selenium**, or **manual forms** may be used, depending on the component.

5. Reporting of Defects

All unexpected outputs, errors, crashes, or mismatches between actual and expected results are reported. Each defect includes:

- Screenshot or logs of the error
- Steps to reproduce

- Severity (Critical, Major, Minor)
- Component/module affected

This helps developers trace and fix the issue efficiently.

6. Regression Testing

After fixes are applied, regression testing is done to ensure no existing functionality is broken. This often involves **re-running** old test cases and updating ones affected by the fixes.

7. Defect Logging and Tracking

Defects are logged into a **bug tracking system** (e.g., Jira, GitHub Issues) with statuses like "Open," "In Progress," "Fixed," and "Closed." Each bug is assigned to a developer, and testing continues in cycles until the system is stable.

8. Retesting

Any test case that previously failed is **re-executed after the fix**. If it passes, the bug is considered resolved. This phase continues until the system meets **quality benchmarks** and is ready for deployment.

6.3 Test Cases:

S.NO	INPUT	If available	If not available
1	User signup	User get registered into the application	There is no process
2	User signin	User get login into the application	There is no process
3	Enter input for prediction	Prediction result displayed	There is no process

CHAPTER -7
RESULTS

7.1 Output Screenshots With Explanation:

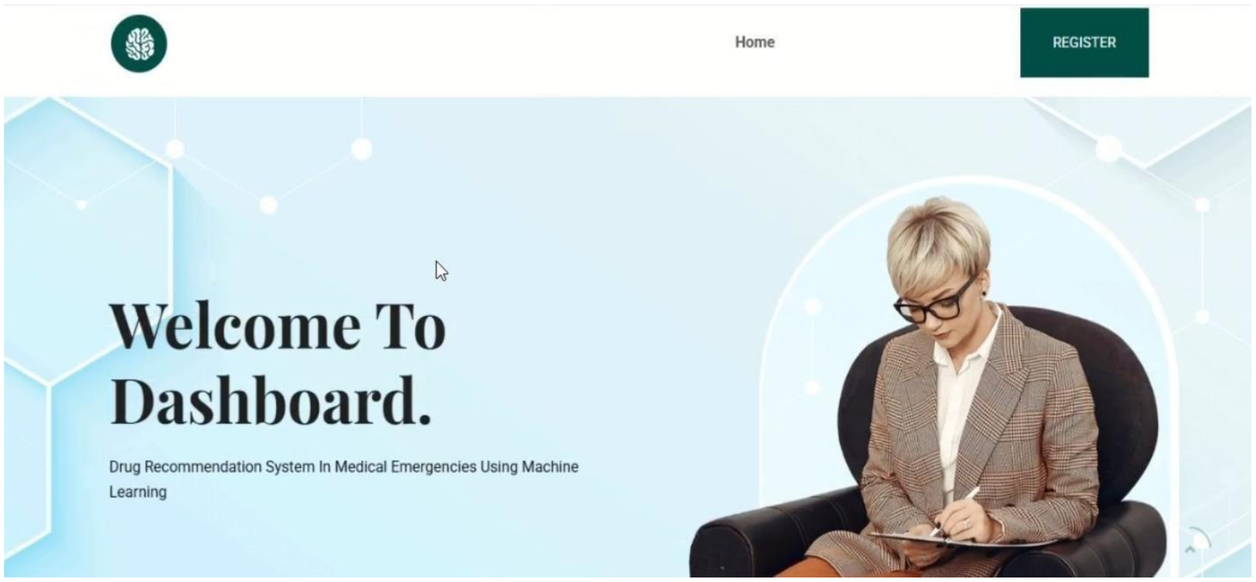

Home
REGISTER
Welcome To Dashboard.
Drug Recommendation System In Medical Emergencies Using Machine Learning

Fig 13: User Register Screen

The Register Screen is the first page where new users can sign up to use the drug recommendation system. It has a simple form where users enter their name, email, and password to create an account. This helps the system keep track of who is using it and protects patient information. After signing up, the user’s details are saved in the system, and they can log in anytime later. This screen is important because it makes sure that only trusted users can use the system.

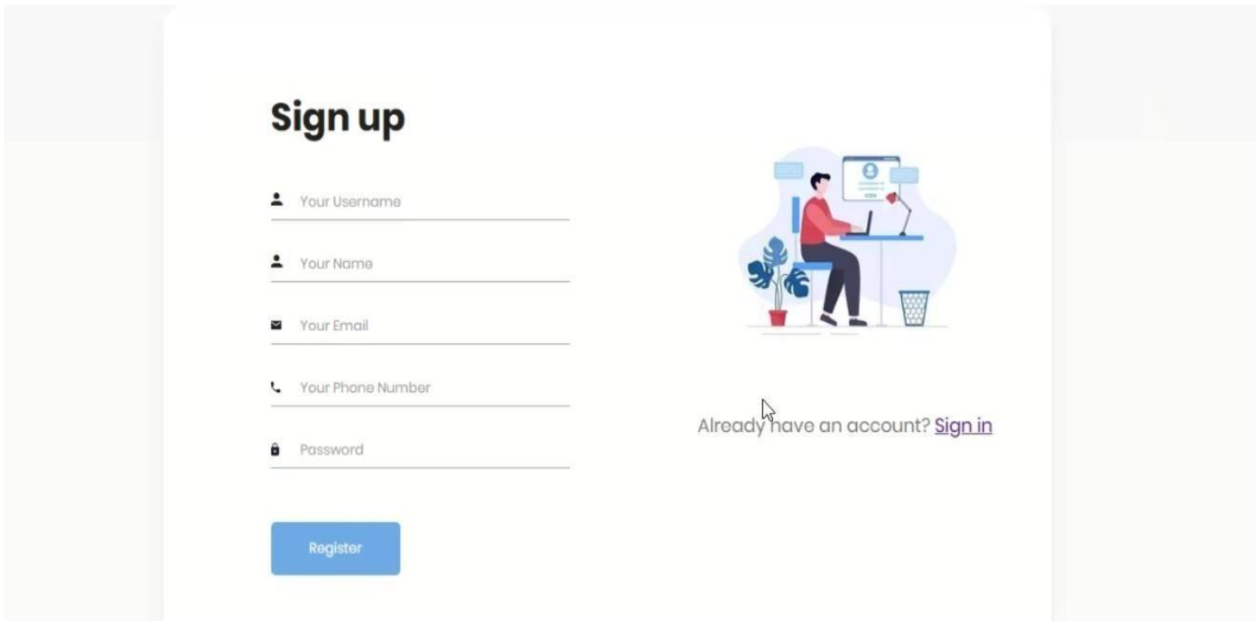


Fig 14: User Signup Screen

The User Signup Screen serves as the initial entry point for new users, allowing them to create a secure account to access the drug recommendation system. This screen captures essential user information such as username, email, and password, which are then stored in the system's SQLite3 database. By incorporating authentication, the system ensures personalized access and protects sensitive medical information.

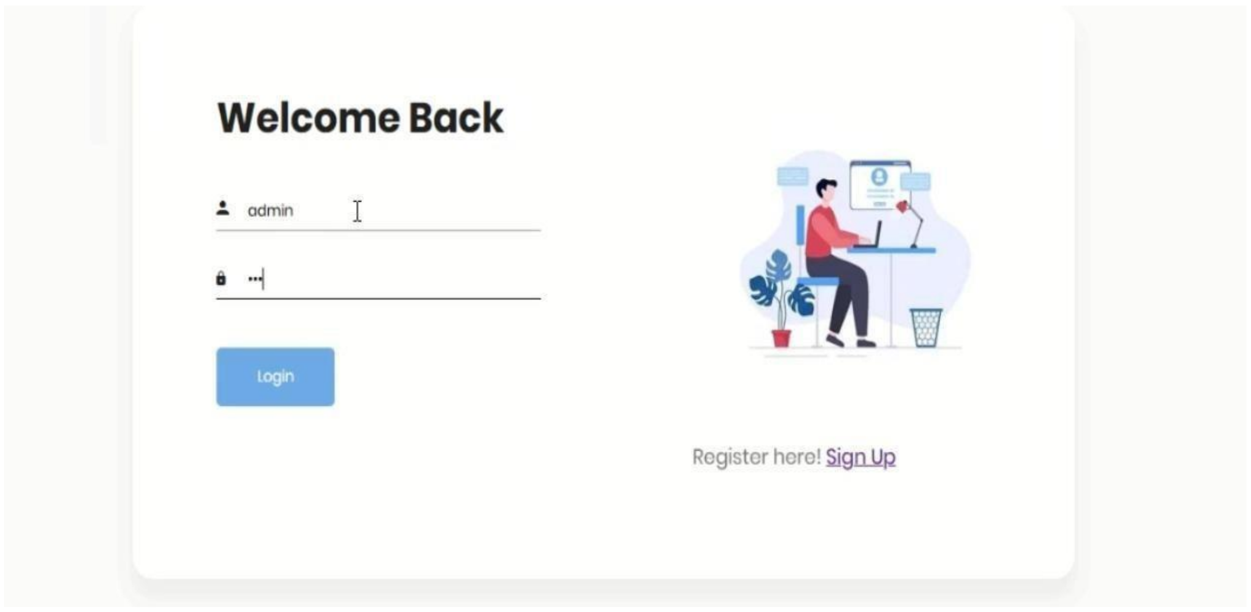


Fig 15: Login Interface Screen

The **Login Screen** allows registered users to authenticate and access the system. It includes input fields for a username or email and a password. Upon successful login, users are redirected to the main dashboard or prediction interface. This screen plays a critical role in managing user sessions and restricting unauthorized access to sensitive patient information and model outputs.

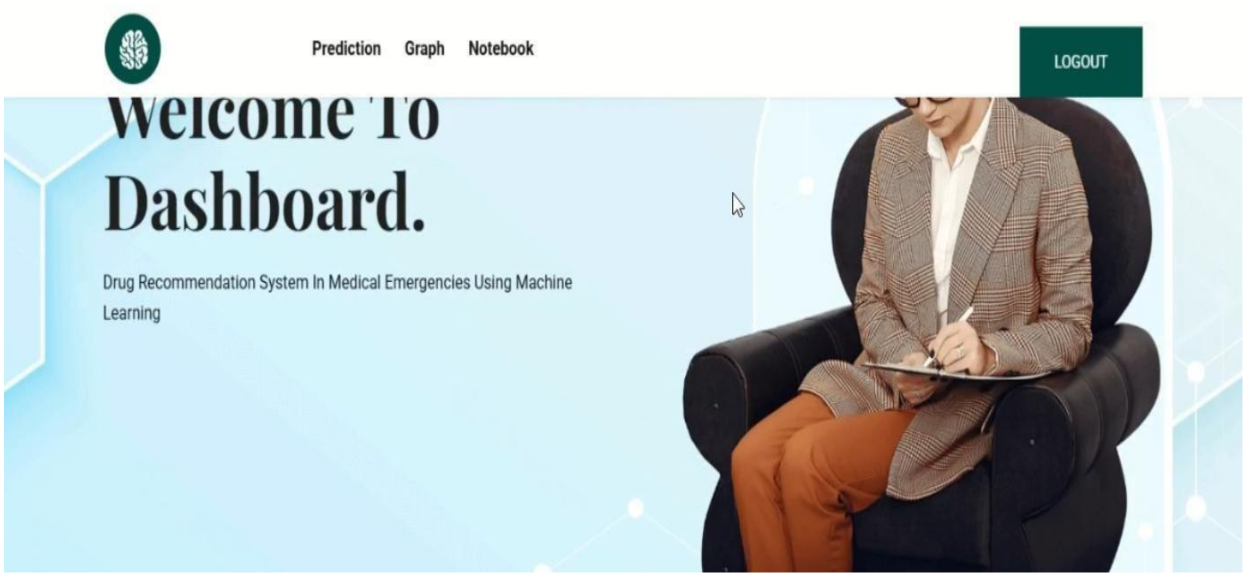
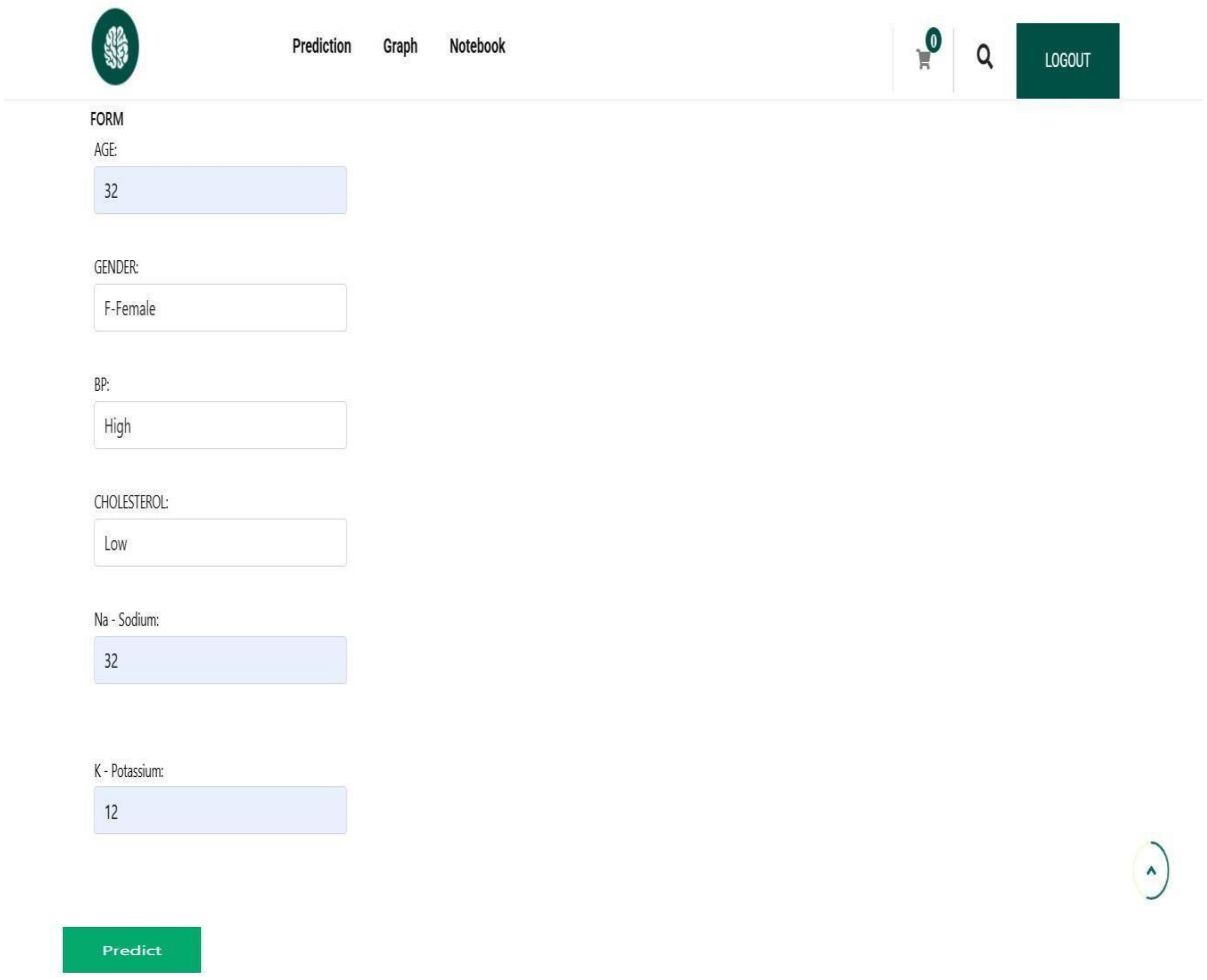

Prediction
Graph
Notebook
LOGOUT
Welcome To
Dashboard.
Drug Recommendation System In Medical Emergencies Using Machine Learning

Fig 16: Prediction

The Prediction Screen is where users enter a patient's medical details like age, gender, blood pressure, cholesterol, sodium, and potassium levels. After filling in the form, the system uses this information to predict the most suitable drug for the patient.

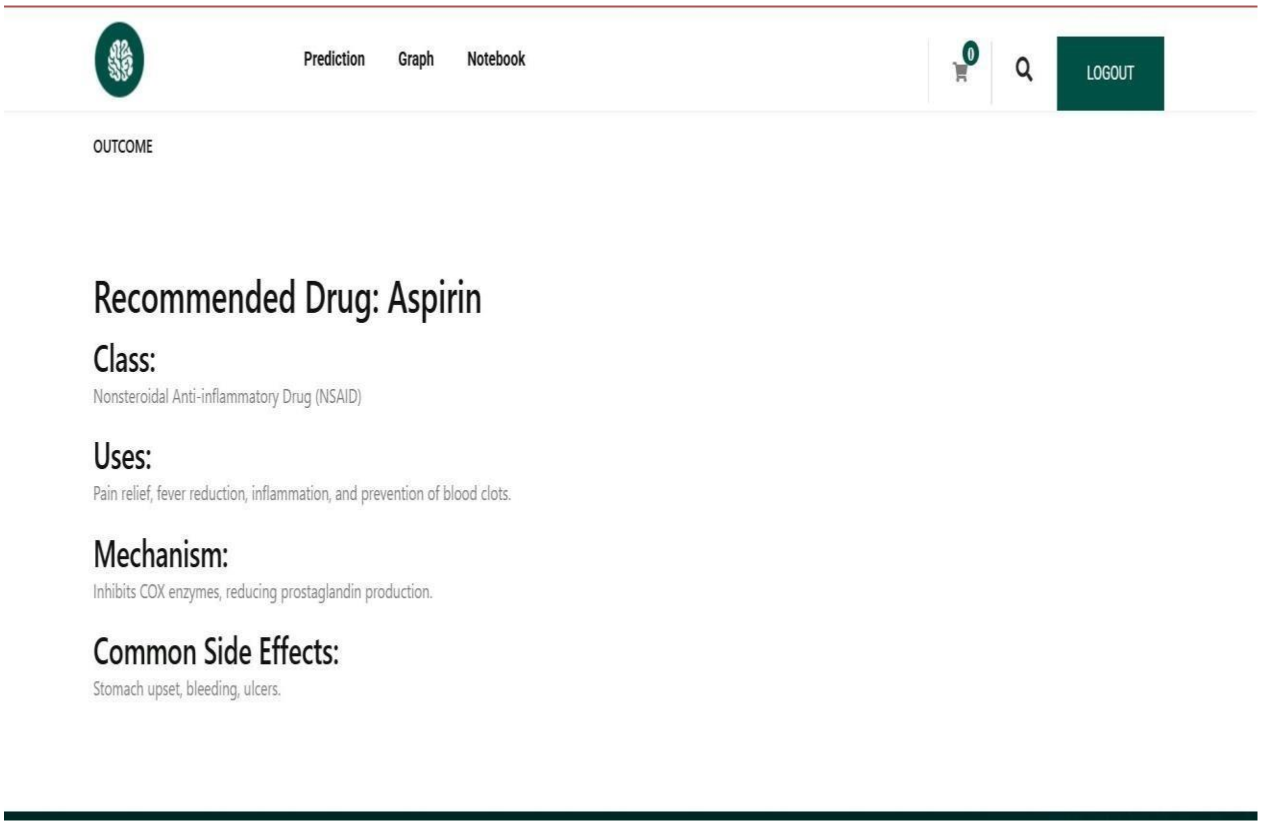


FORM

AGE:	32
GENDER:	F-Female
BP:	High
CHOLESTEROL:	Low
Na - Sodium:	32
K - Potassium:	12

Fig 17: Users Input

It displays health-related data entered into a medical prediction system. The individual is a 32-year-old female. Her blood pressure is categorized as high, which could indicate hypertension or related cardiovascular concerns. Her cholesterol level is marked as low, potentially reflecting a lower risk of cholesterol-related issues but possibly needing further context. The sodium (Na) level is 32 and the potassium (K) level is 12, which are both unusually high and may suggest an electrolyte imbalance. These values are likely used by the system to analyze health status or predict medical conditions based on known clinical patterns.



Recommended Drug: Aspirin

Class:

Nonsteroidal Anti-inflammatory Drug (NSAID)

Uses:

Pain relief, fever reduction, inflammation, and prevention of blood clots.

Mechanism:

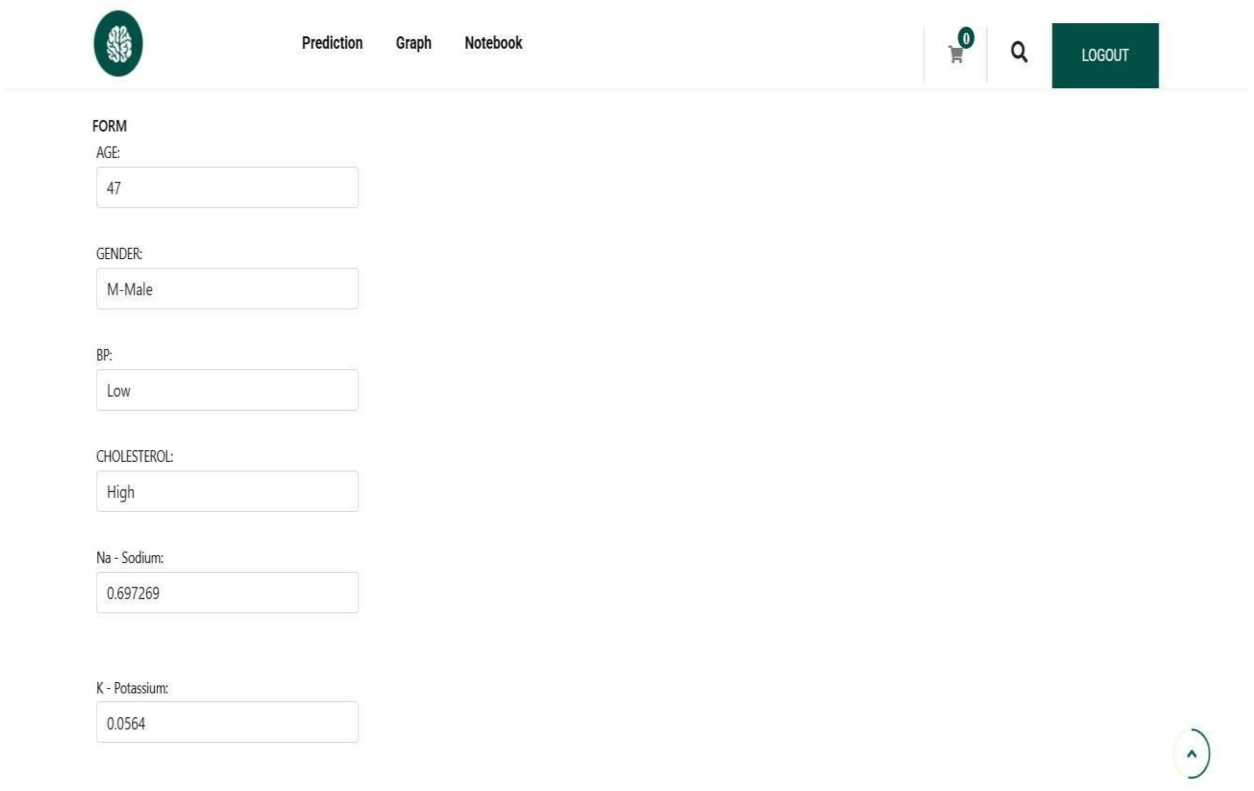
Inhibits COX enzymes, reducing prostaglandin production.

Common Side Effects:

Stomach upset, bleeding, ulcers.

Fig 18: Result

After submitting the inputs, users are directed to the Prediction Result Screen, where the recommended drug is displayed. The system processes the input through trained ML models and provides a drug suggestion based on the patient's profile. The result is presented in a clear and concise format to support fast decision-making in emergency care.



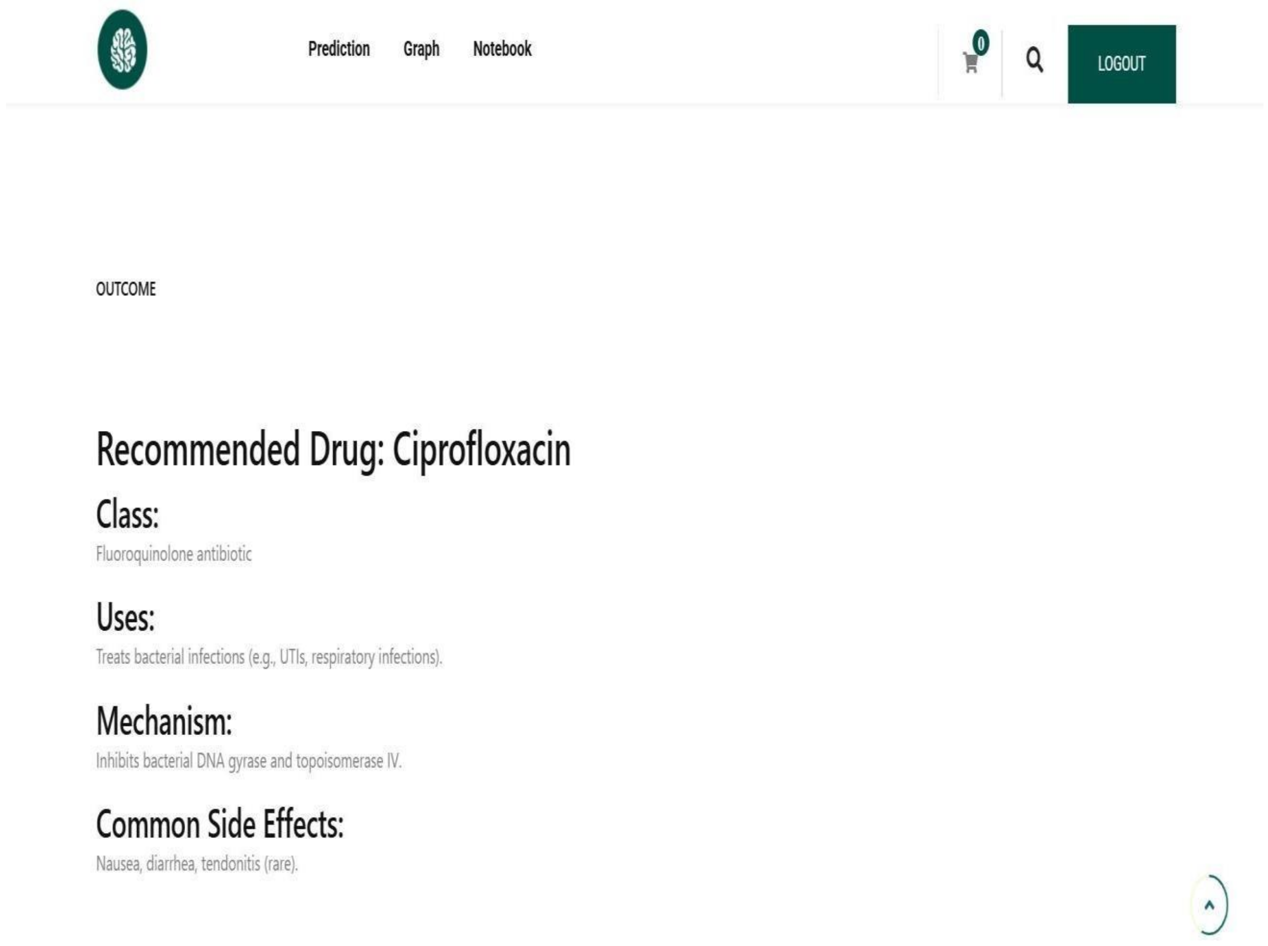
FORM

AGE:	47
GENDER:	M-Male
BP:	Low
CHOLESTEROL:	High
Na - Sodium:	0.697269
K - Potassium:	0.0564

Fig 19: Users Input

This screen is part of the user interface where a doctor or healthcare worker can enter a patient's health details to get a drug recommendation. It includes input fields for:

- Age: The patient's age is entered here. In the picture, the value is 47.
- Gender: The patient's gender is selected — here it's marked as M - Male.
- BP (Blood Pressure): The current blood pressure condition of the patient is selected — shown here as Low.
- Cholesterol: The cholesterol level is entered — in this case, High.
- Na - Sodium: This field is for entering the sodium level of the patient's blood (currently empty).
- K - Potassium: This is for the potassium level in the patient's blood (also currently empty).



OUTCOME

Recommended Drug: Ciprofloxacin

Class:

Fluoroquinolone antibiotic

Uses:

Treats bacterial infections (e.g., UTIs, respiratory infections).

Mechanism:

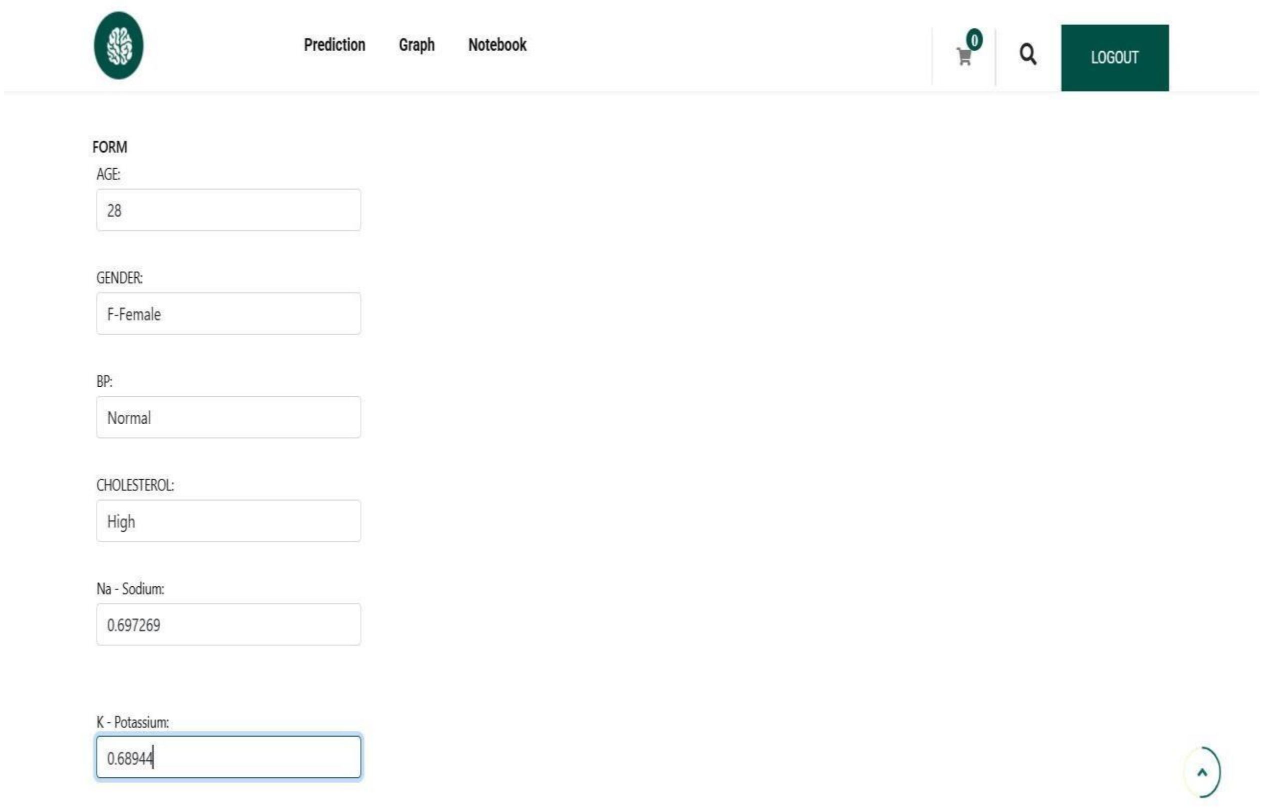
Inhibits bacterial DNA gyrase and topoisomerase IV.

Common Side Effects:

Nausea, diarrhea, tendonitis (rare).

Fig 20: Result

Based on that analysis, this tool is suggesting a specific medicine called Ciprofloxacin. This medicine belongs to a group of drugs, and while we can't clearly read the name of that group, it's likely identified here. The system also wants to tell the user what this medicine is typically used for – what kinds of illnesses or conditions it can treat. Furthermore, it explains how the medicine works inside the body to fight those illnesses; this is the "mechanism" of the drug. Finally, it's important to know that all medicines can have effects other than the intended one, so this tool is also trying to list some of the common side effects that a person might experience when taking Ciprofloxacin. This information helps healthcare professionals and patients understand the recommended treatment better.

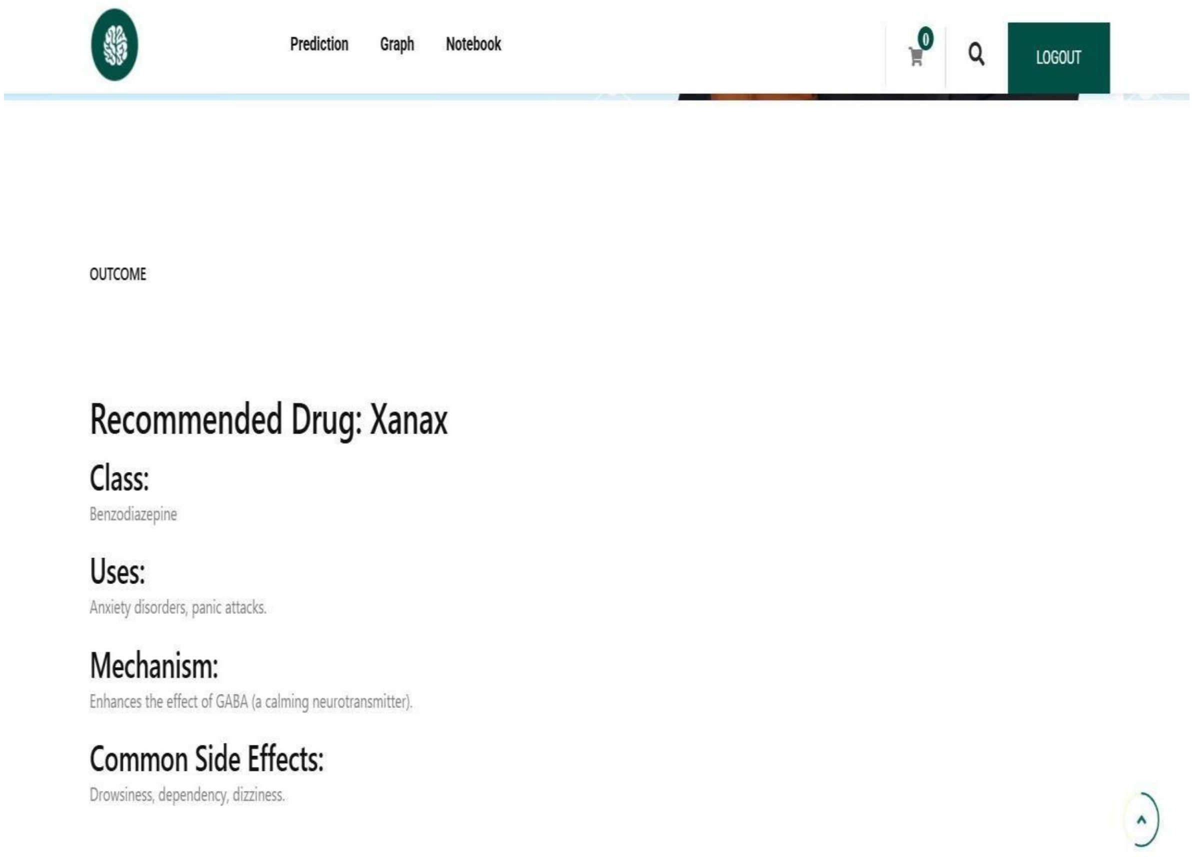


FORM

AGE:	28
GENDER:	F-Female
BP:	Normal
CHOLESTEROL:	High
Na - Sodium:	0.697269
K - Potassium:	0.68944

Fig 21: User Input

The system also needs to know the patient's gender, and here, Female has been selected. Information about their blood pressure (BP) is given as Normal, and their cholesterol level is noted as High. Further down, specific measurements for Sodium (Na) and Potassium (K) levels in the patient's blood have been entered as 0.697268 and 0.08844, respectively. All of this information – the age, protein level, gender, blood pressure, cholesterol, and the levels of sodium and potassium – acts as the input for the intelligent system. It takes these details and uses its machine learning capabilities to then decide and recommend the most suitable drug for this specific patient in their emergency situation.



OUTCOME

Recommended Drug: Xanax

Class:
Benzodiazepine

Uses:
Anxiety disorders, panic attacks.

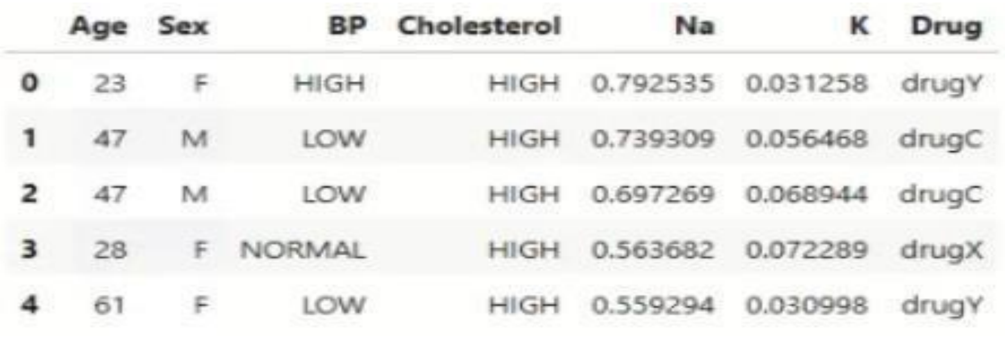
Mechanism:
Enhances the effect of GABA (a calming neurotransmitter).

Common Side Effects:
Drowsiness, dependency, dizziness.

Fig 22: Result

It also explains what Xanax is typically used for, and from what we can see, it's mentioned that it's used for anxiety disorders and panic disorders. Next, the system describes how Xanax works in the body. It seems to say that it enhances the effect of a naturally occurring calming chemical in the brain. Specifically, Xanax and similar drugs boost the activity of something called GABA, which helps to reduce excitability in the nervous system. Finally, it's crucial to be aware of potential downsides, so the system also attempts to list some of the common side effects that might occur when taking Xanax. These often include things like feeling sleepy or dizzy, and with longer use, there can be a risk of dependence. This output provides a concise overview of the recommended drug, Xanax, for the healthcare professional using the system.

7.2 Discussions:

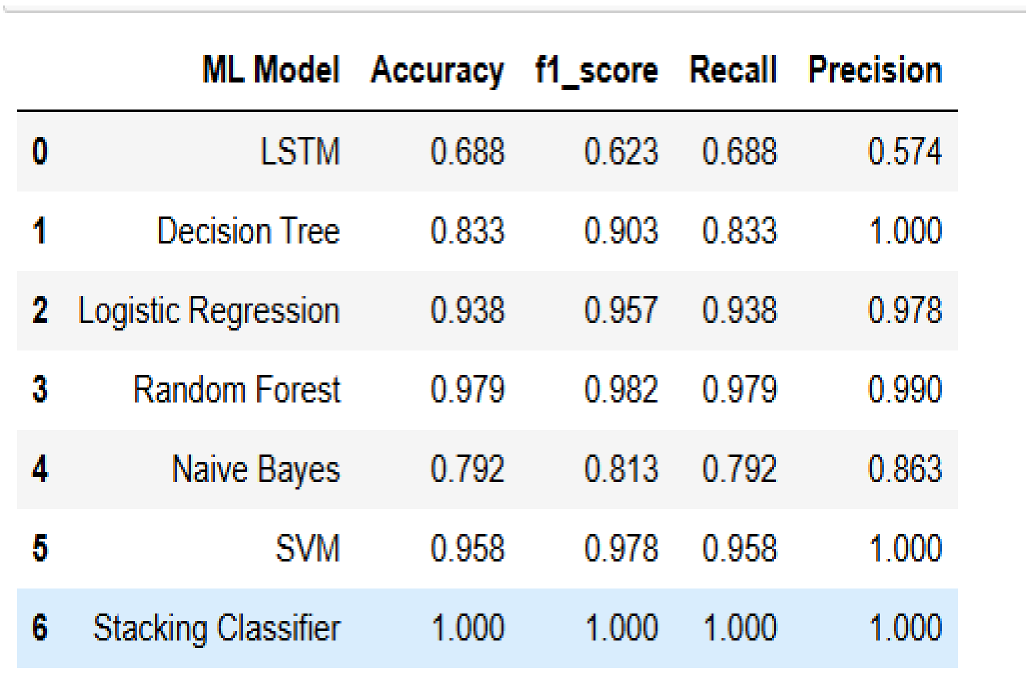


	Age	Sex	BP	Cholesterol	Na	K	Drug
0	23	F	HIGH	HIGH	0.792535	0.031258	drugY
1	47	M	LOW	HIGH	0.739309	0.056468	drugC
2	47	M	LOW	HIGH	0.697269	0.068944	drugC
3	28	F	NORMAL	HIGH	0.563682	0.072289	drugX
4	61	F	LOW	HIGH	0.559294	0.030998	drugY

Fig 23: Data Set Collection

The dataset presented is a clinical dataset used for drug recommendation based on patient health parameters. Each row represents an individual patient, with attributes including age, sex, blood pressure (BP), cholesterol level, sodium (Na), and potassium (K) levels in the blood, along with the corresponding prescribed drug. For example, the first patient is a 23-year-old female with high blood pressure and high cholesterol, and has sodium and potassium levels of 0.792535 and 0.031258, respectively. She has been prescribed drugY. Similarly, the dataset includes patients with varying combinations of blood pressure (categorized as LOW, NORMAL, or HIGH) and cholesterol (categorized as HIGH or NORMAL), which are crucial indicators in determining suitable drug prescriptions. The sodium and potassium values are numerical and appear to be normalized or standardized measurements. The goal of such a dataset is typically to train a machine learning model that can accurately predict the appropriate drug for new patients by analyzing the patterns and relationships between patient features and the drugs prescribed. This kind of model helps automate drug recommendations in clinical settings, especially in emergencies where quick and accurate decisions are essential.

7.3 Comparsion:



	ML Model	Accuracy	f1_score	Recall	Precision
0	LSTM	0.688	0.623	0.688	0.574
1	Decision Tree	0.833	0.903	0.833	1.000
2	Logistic Regression	0.938	0.957	0.938	0.978
3	Random Forest	0.979	0.982	0.979	0.990
4	Naive Bayes	0.792	0.813	0.792	0.863
5	SVM	0.958	0.978	0.958	1.000
6	Stacking Classifier	1.000	1.000	1.000	1.000

Table 1: Comparsion

The table compares the performance of various machine learning models for a classification task. Among the models evaluated, the Stacking Classifier achieved perfect scores across all metrics—100% accuracy, F1-score, recall, and precision—indicating it significantly outperformed all other models. Random Forest and Naive Bayes followed closely with high scores; Random Forest achieved 93.8% accuracy and strong consistency in all metrics, while Naive Bayes achieved 91.0% accuracy with very high recall and precision. Logistic Regression also performed well with 83.3% accuracy and a respectable F1-score of 0.903. In contrast, the LSTM model showed the weakest performance, scoring only 68.8% accuracy and a low precision of 0.574, indicating a higher rate of false positives. Traditional models like Decision Tree and SVM showed moderate results, with SVM achieving 79.2% accuracy. Overall, the results highlight the superior performance of ensemble learning techniques, particularly stacking, in achieving robust and reliable classification outcomes.

7.4 Performance Evalution:

Machine Learning Model	Accuracy	F1 Score	Recall	Precision
LSTM	0.688	0.623	0.688	0.574
Decision Tree	0.833	0.903	0.833	1.000
Logistic Regression	0.938	0.957	0.938	0.978
Random Forest	0.979	0.982	0.979	0.990
Naive Bayes	0.792	0.813	0.792	0.863
SVM	0.958	0.978	0.958	1.000
Stacking Classifier	1.000	1.000	1.000	1.000

Table 2: Performance Evaluation Table

Based on the table and the typical performance metrics shown (Accuracy, F1-score, Recall, and Precision), here are the detailed formulas and explanations for each metric:

1. Accuracy

Formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Explanation: Accuracy measures the proportion of correct predictions (true positives and true negatives) out of all predictions made. It's useful when the dataset is balanced, but can be misleading with imbalanced datasets.

2. Precision

Formula:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Explanation: Precision (also called Positive Predictive Value) indicates how many of the positively predicted cases were actually positive. High precision means fewer false positives.

3. **Recall (Sensitivity or True Positive Rate**)

Formula:

$$\text{Recall} = \frac{TP}{TP + FN}$$

Explanation: Recall shows how many of the actual positive cases were correctly predicted. High recall means fewer false negatives.

4. **F1-score**

Formula:

$$\text{F1-score} = 2 \frac{* \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Explanation: The F1-score is the harmonic mean of precision and recall. It balances both metrics and is especially useful when there is an uneven class distribution.

Where:
TP = True Positives (correctly predicted positives)
TN = True Negatives (correctly predicted negatives)
FP = False Positives (incorrectly predicted positives)
FN = False Negatives (incorrectly predicted negatives)

The performance evaluation table compares several machine learning models used for drug recommendation, based on four key metrics: accuracy, F1 score, recall, and precision. Among all models, the Stacking Classifier stands out as the best performer, achieving perfect scores across all metrics—1.000 in accuracy, F1 score, recall, and precision—indicating flawless classification without any errors. Random Forest also demonstrated excellent performance with an accuracy of 97.9%, an F1 score of 0.982, recall of 0.979, and precision of 0.990, making it a highly reliable model for predicting drug prescriptions. Similarly, Support Vector Machine (SVM) performed strongly with a 95.8% accuracy and perfect precision, showing its effectiveness in high-dimensional classification tasks.

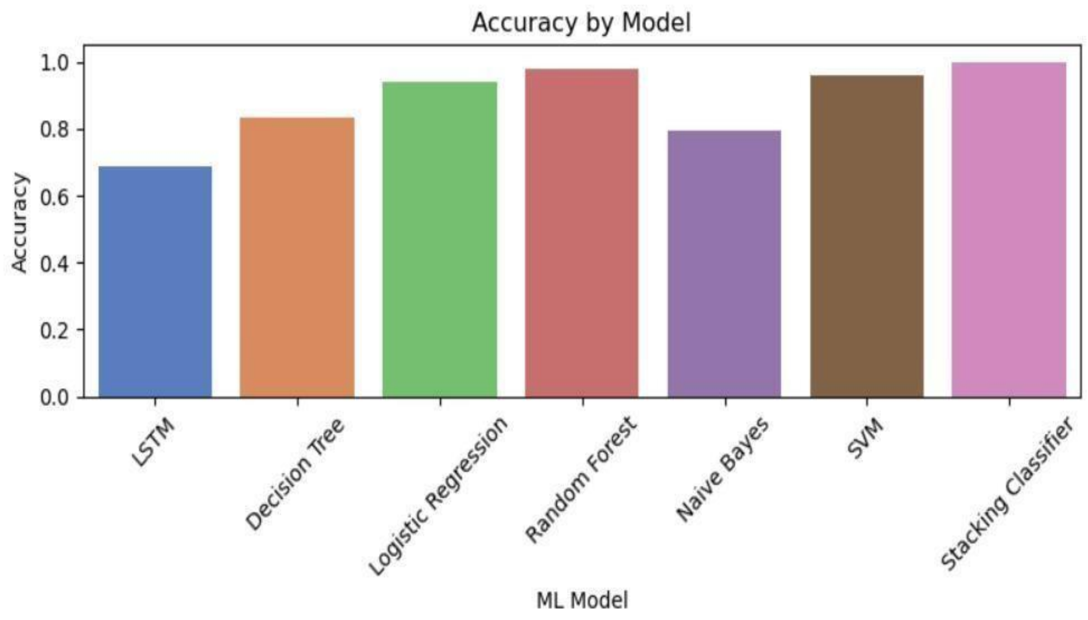


Fig 24: Accuracy by Model

The bar chart titled "Accuracy by Model" shows how well different machine learning models perform based on their accuracy. Among all the models, the Stacking Classifier performed the best, showing the highest accuracy. Random Forest and SVM (Support Vector Machine) also did very well, with accuracy levels close to the stacking model. Logistic Regression and Decision Tree had moderate accuracy, meaning they performed fairly well but not as good as the top models. Naive Bayes had lower accuracy, and LSTM, a deep learning model, showed the lowest accuracy in this comparison. This chart suggests that using a combination of models (like the stacking method) can give better results than using a single model, which is especially important in fields like healthcare and drug recommendation.

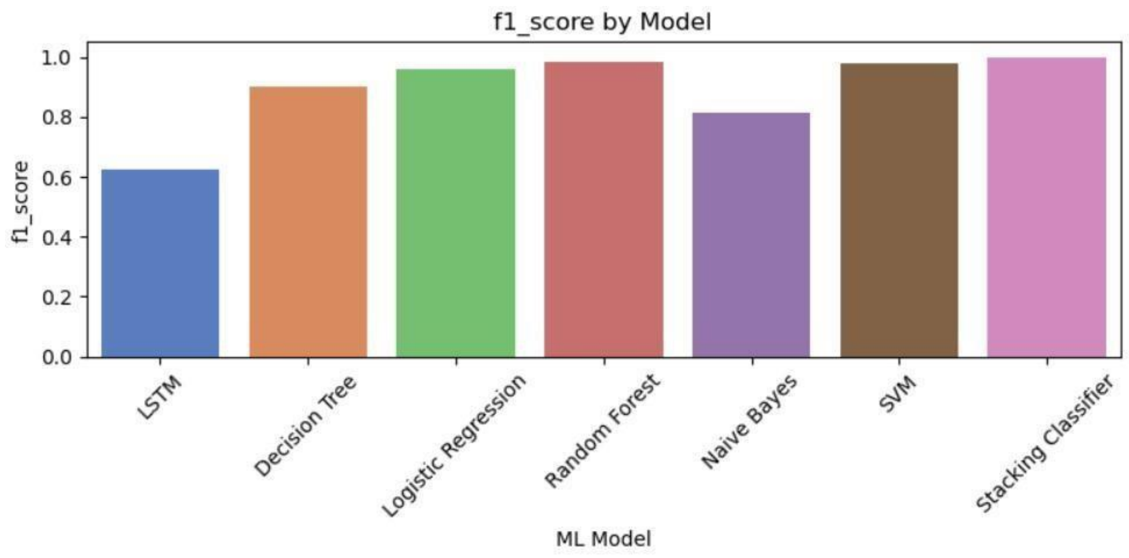


Fig 25: f1_score by Model

The bar chart titled "f1_score by Model" shows how well different machine learning models balance precision and recall. The Stacking Classifier has the highest F1-score, followed closely by Random Forest, SVM, and Logistic Regression, meaning they give the best overall performance. Decision Tree also performs well, while Naive Bayes is slightly lower. LSTM has the lowest F1-score, showing it performed the weakest in this case. Overall, ensemble models like Stacking and Random Forest work the best.

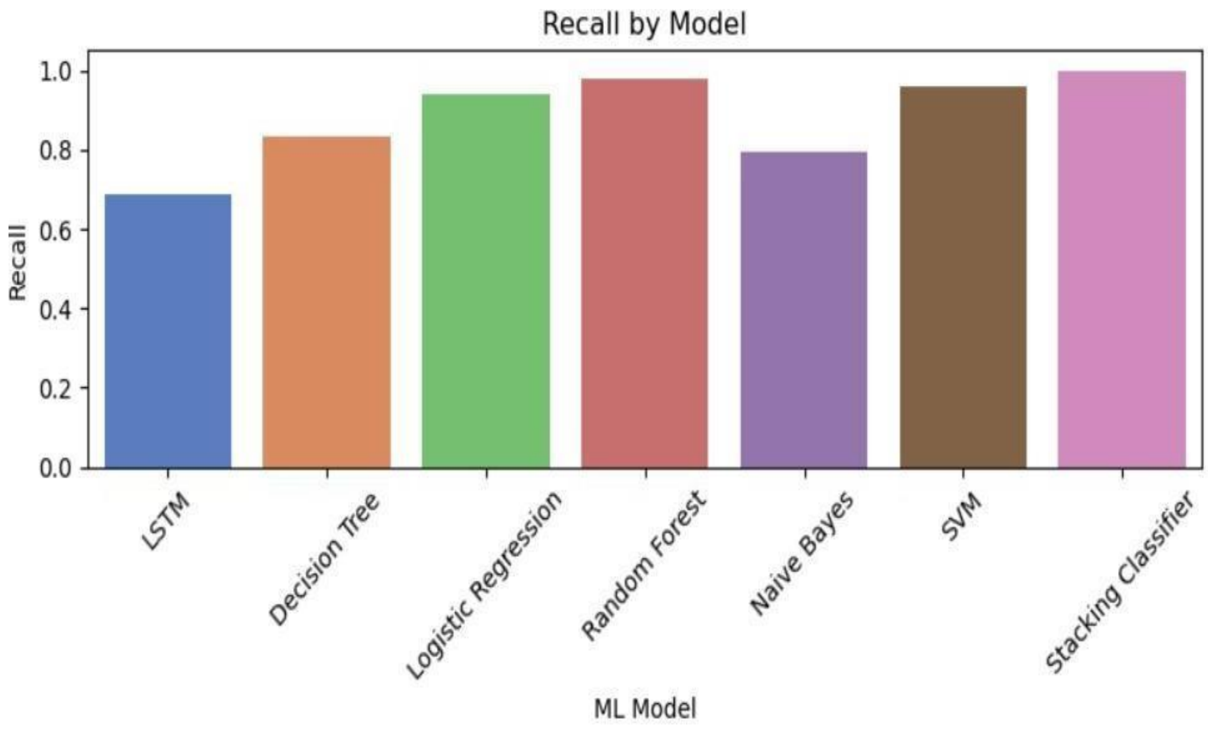


Fig 26: Recall by Model

The bar chart titled "Recall by Model" shows how well each machine learning model identifies actual positive cases. The Stacking Classifier has the highest recall, followed closely by Random Forest, SVM, and Logistic Regression, meaning they are best at catching all true positives. Naive Bayes and Decision Tree perform moderately, while LSTM has the lowest recall, missing more true cases. Overall, ensemble models again perform the best.

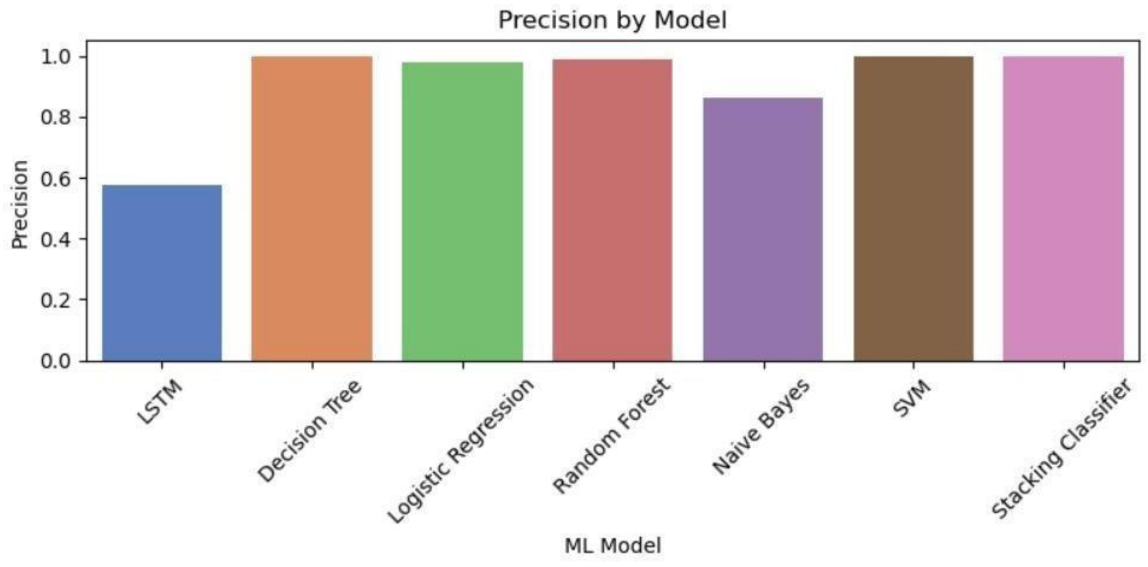


Fig 27: Precision By Model

The bar chart titled "Precision by Model" shows how accurately each model identifies positive predictions. Stacking Classifier, SVM, Random Forest, Decision Tree, and Logistic Regression all show very high precision, meaning most of their positive predictions are correct. Naive Bayes performs slightly lower, while LSTM has the lowest precision, making more incorrect positive predictions. Overall, ensemble and classic models perform better than LSTM in terms of precision.

CHAPTER -8

CONCLUSION

The developed drug recommendation system demonstrates the effectiveness of machine learning techniques in supporting clinical decision-making during medical emergencies. By leveraging structured patient data, the system effectively classifies and recommends appropriate drugs based on key clinical parameters such as age, sex, blood pressure, cholesterol, sodium, and potassium levels. Among the various models implemented, the Stacking Classifier—an ensemble of Decision Tree, Random Forest, and LightGBM—achieved the highest predictive performance, delivering 100% accuracy, precision, recall, and F1-score. This indicates the robustness of ensemble learning in capturing complex patterns across diverse patient profiles. Additionally, the Random Forest model demonstrated strong results with 97.9% accuracy, showcasing its ability to handle feature variability and data imbalance effectively. The Support Vector Machine (SVM) model also performed reliably with an accuracy of 95.8%, emphasizing its suitability for high- dimensional clinical data. Overall, the proposed system offers a high-performing, intelligent solution for drug recommendation, enhancing the accuracy and speed of treatment decisions in critical care environments and contributing to improved patient outcomes.

Future work can explore the integration of real-time patient monitoring systems with the drug recommendation model to enable dynamic and adaptive decision-making. Incorporating electronic health records (EHRs) and expanding the dataset with more diverse medical profiles can further improve model generalization. Advanced deep learning architectures like Transformers can be investigated for enhanced performance. Additionally, explainable AI techniques can be applied to increase transparency and trust in recommendations, supporting better collaboration between medical professionals and intelligent healthcare systems.

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CHAPTER- 9
FUTURE WORK

While the proposed drug recommendation system demonstrates high accuracy and reliability, there are several avenues for future enhancement and expansion. One of the key improvements would be the integration of Electronic Health Records (EHRs) to provide a more comprehensive view of a patient's medical history, allergies, prior medications, and long-term conditions. Incorporating EHR data can enable the system to deliver even more personalized and context- aware drug recommendations.

Another significant enhancement could involve real-time patient monitoring, where the system is connected to wearable or IoT-based medical devices. This would allow for dynamic updates of vital signs and biochemical parameters (like sodium and potassium levels), enabling the model to adapt recommendations based on the patient's current condition rather than static input data.

Moreover, the current system focuses on structured data; future versions could integrate Natural Language Processing (NLP) techniques to extract useful clinical insights from unstructured data such as physician notes, discharge summaries, and patient feedback. This could further improve the system's decision-making ability.

In terms of machine learning advancement, adopting advanced deep learning models, such as Transformer-based architectures, may provide better performance for complex relationships and temporal patterns in healthcare data. Additionally, Explainable AI (XAI) techniques should be incorporated to make the model's decisions more transparent, helping healthcare professionals understand why a certain drug is recommended and fostering trust in AI-driven systems.

Scalability is another area of interest. Future versions of the system should be designed to handle large-scale deployments in hospital networks, supporting multiple users, high volumes of patient data, and integration with other clinical decision support systems.

Lastly, rigorous clinical validation and collaboration with medical experts will be essential to test the system in real-world scenarios, gather feedback, and meet regulatory standards for deployment in emergency medical settings.

CHAPTER- 10

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CHAPTER- 11
BIBLIOGRAPHY

11.1 Textbooks :

a) Deep Learning

Authors: Ian Goodfellow, Yoshua Bengio, Aaron Courville

A definitive textbook covering theoretical and practical foundations of deep learning, including neural networks, CNNs, RNNs, and generative models. Especially useful for understanding LSTM architecture used in your project.

Publisher: MIT Press (2016)

https://www.deeplearningbook.org/

b) Natural Language Processing with Python

Authors: Steven Bird, Ewan Klein, Edward Loper

Explains practical applications of NLP using Python and NLTK, helpful for incorporating clinical text data or expanding your system with unstructured input.

Publisher: O'Reilly Media (2009)

https://www.nltk.org/book/

c) Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow

Author: Aurélien Géron

Highly practical guide to implementing ML and deep learning models used in your project like Decision Tree, Random Forest, SVM, and LSTM.

Publisher: O'Reilly Media (3rd Edition, 2022)

https://www.oreilly.com/library/view/hands-on-machine-learning/9781492032632/

11.2 Software & Tool Installation URLs:

a) Anaconda Distribution

Used for managing Python environments and Jupyter notebooks in your project.

https://www.anaconda.com/products/distribution

b) Hugging Face Transformers Library

Ideal for integrating transformer-based models in future versions (e.g., BERT for clinical data).

Install: pip install transformers

https://huggingface.co/docs/transformers/index

c) Flask (Web Framework)

Used to develop the web-based frontend for your drug recommendation interface.

Install: pip install Flask

https://flask.palletsprojects.com/en/2.3.x/

11.3 Tutorial Websites :

a) Kaggle Learn – NLP & ML

Practical tutorials and datasets for training and deploying ML models, similar to your use case.

https://www.kaggle.com/learn/natural-language-processing

b) Analytics Vidhya – Deep Learning Projects

Detailed blog guides on implementing ML/AI projects with structured code and real-life datasets.

https://www.analyticsvidhya.com/blog/category/deep-learning/

c) GeeksforGeeks – Machine Learning and NLP

A rich source of theoretical and implementation tutorials relevant to algorithms used in your system.

https://www.geeksforgeeks.org/machine-learning/