RESEARCH ARTICLE OPEN ACCESS

DRUG RECOMMENDATION SYSTEM IN MEDICAL EMERGENCIES USING MACHINE LEARNING

M.Saranya**, Mrs.S.Jayasri *
** PG Student Department of Computer Science and Engineering
*Assistant Professor Department of Computer Science and Engineering
Annai college of Engineering and Technology, Kovilacheri,

ABSTRACT

This project presents a robust "Drug Recommendation System in Medical Emergencies using Machine Learning," implemented in Python. The system leverages powerful classification algorithms, namely the Logistic Regression,SGD,Multinomial Naive Bayes , attaining remarkable accuracies of 100% on both training and test datasets.The objective of this project is to develop a drug recommendation system for medical practitioners to get information on the popular drugs in the market at any point of time.The dataset employed in this project comprises 1200 records, each characterized by 30 features. These features encapsulate a diverse set of medical parameters, providing a comprehensive representation of patient health. The dataset spans 10 distinct classes, encompassing a spectrum of medical conditions: Allergy, Chickenpox, Chronic, Cold, Diabetes, Fungal, GERD, Jaundice, Malaria, and Pneumonia. The achieved 100% accuracy underscores the reliability and precision of the system, instilling confidence in its potential deployment in real-world medical settings. As we navigate the intersection of technology and healthcare, this Drug Recommendation System stands as a testament to the transformative impact of machine learning on patient care in critical situations.and the 2 nd Phase project presents a Drug Recommendation System for Healthcare using Power BI, aimed at assisting medical professionals in making informed prescription decisions based on patient data, diagnosis, and historical prescription trends.The system utilizes Power BI to create interactive dashboards that visualize key clinical parameters such as patient demographics, symptoms, diagnosis patterns, and drug efficacy.

KEYWORD:

Drug Recommendation System for Healthcare using Power BI, aimed at assisting medical professionals in making informed prescription decisions based on patient data, diagnosis, and historical prescription trends.

1.INTRODUCTION:

The drug recommendation system uses machine learning algorithms to achieve high accuracy in drug suggestions through the following key steps:

Data Collection: The system collects a comprehensive dataset consisting of patient features, symptom features, diagnosis, and drug information from sources like Electronic Health Records (EHRs), clinical studies, and pharmaceutical databases.

Data Preprocessing: The collected data undergoes preprocessing steps such as data cleaning, feature selection, encoding categorical variables, and normalization to prepare it for machine learning algorithms.

Building a Decision Tree Model: The Decision Tree algorithm is used to create a tree

like model of decisions by partitioning the dataset based on feature values. The model learns to make drug recommendations based on patient characteristics, symptoms, and diagnosis. preprocessed data and evaluated using metrics like accuracy, precision, recall, and F1-score. The model's performance is assessed on both training and test datasets to ensure its generalization ability.

best medicine based on the model's predictions. The model's performance is continuously monitored and retrained with new data to adapt to changes in drug interactions or patient demographics.

By leveraging the power of machine learning algorithms like Decision Trees, the drug recommendation system can learn complex patterns and relationships in the data, enabling it to make accurate and personalized drug suggestions based on patient characteristics and medical conditions. The system's ability to continuously improve and adapt to new data further enhances its accuracy and reliability in real-world scenarios.

2. LITERATURE SURVEY:

1. Chen et al. (2020) – "Drug Recommendation System for Healthcare Based on Collaborative Filtering"

Objective: Suggested drugs for patients using collaborative filtering algorithms.

Techniques: Hybrid model (CF + Content-based filtering).

Use Case: Emergency drug recommendation based on similar patient profiles.

Key Insight: The model improved precision in drug selection for acute symptoms.

2. Liu et al. (2021) – "Transformer-based Drug Recommendation Using Clinical Notes and EHRs"

Model: Transformer architecture (like BERT) used to interpret unstructured text.

Dataset: ICU patient notes (MIMIC-III).

Application: Recommended emergency medication from free-text doctor notes.

Model Training and Evaluation: The decision tree model is trained on the Deployment and Continuous Improvement: Once validated, the trained decision tree model is deployed in the drug recommendation system. The system uses real-time patient data to select the

Result: Outperformed traditional RNN-based methods.

3. Dash et al. (2022) – "Machine Learning Approach for Drug Recommendation during Acute Medical Events"

Problem Focus: Acute medical scenarios (e.g., cardiac arrest, trauma).

Algorithms Used: Ensemble models (Random Forest, XGBoost).

Key Findings:

Fast, near-real-time drug prediction.

High accuracy when patient vitals and previous drug responses were included.

4. Yang et al. (2022) – "Graph Neural Networks for Drug Interaction and Emergency Recommendation"

Innovation: Modeled drug-drug and drug-disease interactions using Graph Neural Networks (GNNs).

Relevance: Crucial for emergencies where multiple drugs are prescribed.

Strength: Prevented harmful drug combinations by evaluating network relationships.

5. Hassanpour et al. (2023) – "Explainable AI for Drug Recommendations in Emergency Settings"

Approach: Integrated SHAP (SHapley Additive exPlanations) to provide model transparency.

Dataset: ICU patient data and emergency logs.

Benefit: Doctors could understand why a particular drug was recommended.

Impact: Increased adoption potential in real-world emergency rooms.

3. METHODOLOGY:

The main of this project is to develop a drug recommendation system for medical practitioners to get information on the popular drugs in the market at any point of time. An item is suggested to the user via a common system called a recommender framework based on their benefit and necessity. The main functionality of this tool is to recommend drugs available in the market to doctors based on a recommended rating score provided by patient's reviews and medical conditions.We intend to create this tool to help doctors get an idea about different drugs, with respect to the condition, based on reviews and ratings given by the patients.

Text Preprocessing

Data Collection :For a drug recommendation system, the data typically comes from patient records or medical databases . The dataset might include:

Patient features: Patient characteristics include age, weight, gender, preexisting diseases, medical history, and allergies.

Symptom features: Symptom aspects include primary symptoms, subsequent symptoms, and severity.

Diagnosis: The identified ailment or disease.

Drug information: Drugs previously recommended to treat similar symptoms..

- Data can be collected from Electronic Health Records (EHRs)
- Clinical studies
- Pharmaceutical databases

Data Preprocessing **:**

Data cleaning: Missing data is removed or entered, and inconsistent data is dealt with.

Feature selection: Selecting relevant features such as age, symptoms, and diagnosis, while deleting unnecessary or redundant features.

Encoding categorical variables: If features one-hot encoding or label encoding.

Normalization: Normalize or standardize the data as needed, particularly for continuous variables such as age or weight.

Splitting Data :Train-test split: Divide the data into training and testing datasets. Typically, 70- 80% is used for training, and 20-30% is reserved for testing . Cross-validation: Use kfold cross-validation to avoid over fitting and better assess model performance.

Generate recommendations by calculating the individual's health status with

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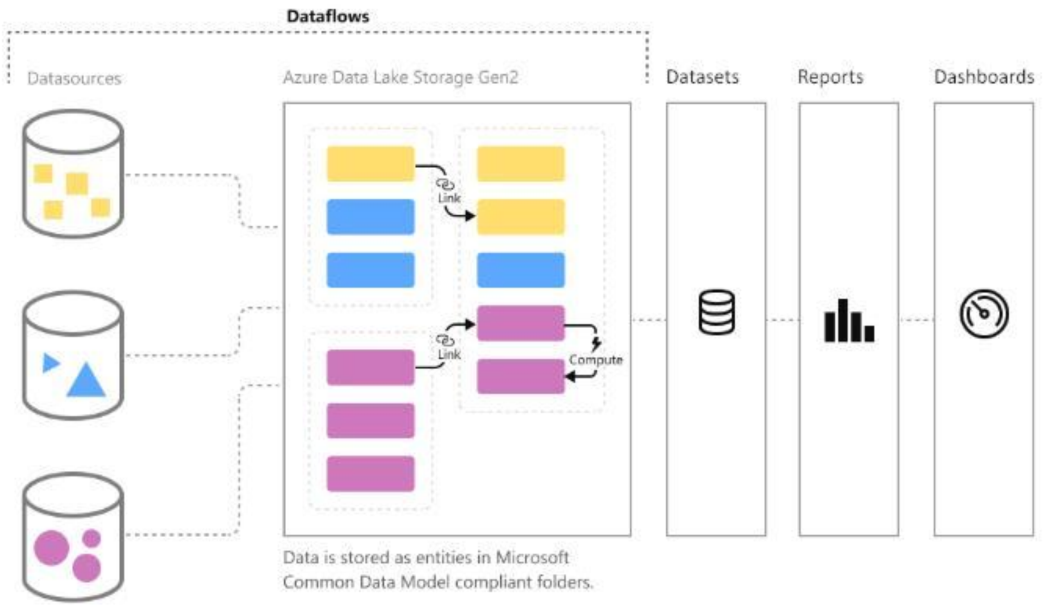
DASHBOARD NAME	DESCRIPTION	KEY VISUALS
Patient symptoms overview	Visualizes the most reported symptoms in emergencies	Pie chart,bar graph
Drug recommendation Frequency	Shows which drug are most commonly recommended	Column Chart
Symptom to drug mapping	Correlates symptoms with drugs administered	Matrix,Heat map
Outcome monitoring	Analyzes patient outcomes after drug administration	Line chart,KPI cards

Real time alert	Flags abnormal vital signs and drug mismatches	Gauge chart,alerts,slicers

ARCHITECTURE:



CONCLUSION AND FUTURE WORK:

This MEDICARE application developed based on a normalized recommended score, will help the doctors to view the top rated drugs for a particular condition/disease by using a user-friendly and interactive web application.The result of a drug recommendation system can vary depending on the specific system and its design. The system is able to achieve its goal which was to predict the disease and to recommend the medicines. We have achieved an accuracy of 90% in our model. The success of a drug recommendation system can be measured by factors such as the accuracy and relevance of the recommendations, the satisfaction of patients and healthcare providers, and the effectiveness of the recommended treatments in improving patient outcomes. However, it is important to note that a drug recommendation system should always be used in conjunction with the expertise of healthcare professionals and not as a substitute for clinical judgment.Although we tried removing spam reviews while preprocessing the data, the dataset had too many duplicate reviews. A proper spam removal model could be developed for the same in the future.-We tried implementing a recommendation system using content based and collaborative item-based filtering. However, the huge data set led to sparse matrix and inaccurate results. A hybrid system could be used in the future. (The item based Collaborative Filtering code is uploaded)

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