**TITLE**

*****DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING,***

***SCHOOL OF ENGINEERING AND TECHNOLOGY, SHARDA UNIVERSITY, GREATER NOIDA***

**COLLABORATIVE FILTERING-BASED DRUG RECOMMENDATION USING**

**MACHINE LEARNING TEQNIQUES**

***A project submitted***

***in partial fulfillment of the requirements for the degree of Bachelor of Technology in Computer Science and Engineering***

**by**

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# CERTIFICATE

This is to certify that the report entitled **“Collaborative filtering based drug recommendation system using the machine learning technique”** submitted by **“**RAGHVENDRA PRATAP MAURYA (2019664831) and NIBBRITTA NILOY SARKER (2019008292)**”** to Sharda University, towards the fulfillment of requirements of the degree of **“Bachelor of Technology”** is record of bonafide final year Project work carried out by them in the **“**Department of Computer Science & Engineering, School of Engineering and Technology, Sharda University**”**.

The results/findings contained in this Project have not been submitted in part or full to any other University/Institute for award of any other Degree/Diploma.

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# ACKNOWLEDGEMENT

A major project is a golden opportunity for learning and self-development. We consider our self very lucky and honored to have so many wonderful people lead us through in completion of this project.

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# ABSTRACT

Collaborative filtering is a widely used technique in recommendation systems. In the domain of healthcare, it can be used to suggest drugs to patients based on their medical history and preferences. In this paper, we propose a collaborative filtering-based drug recommendation system using machine learning techniques.

The system takes into account the patient's medical history, current medications, and demographic information such as age and gender to suggest drugs. We use a hybrid approach, combining content-based filtering and collaborative filtering techniques, to improve the accuracy of the recommendations.

The system is trained on a large dataset of patient medical records and drug prescriptions, and uses a variety of machine learning algorithms to identify patterns in the data. The algorithms are trained to predict which drugs a patient is likely to respond well to, based on their medical history and demographics.

To evaluate the system, we conducted a series of experiments using real-world patient data. The results show that our system outperforms existing drug recommendation systems in terms of accuracy and efficiency. Our system also has the advantage of being able to adapt to changes in the patient's medical history and preferences over time.

In addition to drug recommendations, our system also provides information on potential adverse drug reactions and drug interactions. This information is derived from a database of known drug interactions and adverse effects, which is continuously updated with new data.

Overall, our system represents a significant advance in the field of drug recommendation systems. By combining collaborative filtering and machine learning techniques, we are able to provide accurate and personalized drug recommendations to patients, improving their health outcomes and quality of life.

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# CHAPTER 1 INTRODUCTION

## Problem Statement

The healthcare industry is constantly evolving, with new drugs being introduced to the market regularly. However, with the increasing number of available drugs, it has become challenging for patients to select the most suitable medicine for their condition. Moreover, patients often rely on their doctors' recommendations, who may not have complete information about all available drugs.

To address this issue, the Collaborative Filtering Drug Recommendation System using machine learning techniques has been proposed. The project aims to develop a system that recommends drugs to patients based on their medical history, symptoms, and other relevant factors. The system will use collaborative filtering techniques to generate personalized drug recommendations for each patient.

One of the major challenges in developing such a system is the lack of a standard format for medical records. The project will need to address this issue by developing a data standardization process that can convert medical records into a consistent format suitable for analysis. Another challenge is the sparsity of data. Medical records often have incomplete information, making it difficult to generate accurate recommendations.

To overcome this challenge, the project will use machine learning algorithms such as k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Tree to analyze patient data and generate personalized drug recommendations. The project will also explore the use of natural language processing techniques to extract relevant information from patient reviews and feedback.

The success of the proposed system will be evaluated based on the accuracy and effectiveness of the drug recommendations generated. The system's performance will be compared with existing drug recommendation systems to demonstrate its efficacy. Moreover, the project will also investigate the system's scalability to ensure it can handle large volumes of patient data.

Drug recommendation systems have become increasingly popular in recent years as healthcare professionals face growing pressure to provide effective and efficient care to their patients. With a vast amount of information available on various medications, it can be challenging for healthcare providers to keep up with the latest advancements and determine the best treatment options for their patients. This is where drug recommendation systems come into play.

The purpose of this drug recommendation project is to develop a reliable and accurate drug recommendation system that can assist healthcare professionals in making informed decisions about the best medications for their patients. The system outlined in this synopsis will evaluate patient data using AI and machine learning algorithms and offer tailored medicine recommendations based on their medical history and symptoms.

The need for such a system has become more critical as medication errors and adverse drug reactions continue to be a significant problem in healthcare. According to the National Academies of Sciences, Engineering, and Medicine report, over 1.5 million Americans have prescription errors every year, which can have serious consequences. costs and negative health outcomes. By utilizing machine learning algorithms and natural language processing techniques, this drug recommendation system can help healthcare professionals reduce the risk of medication errors and improve patient outcomes.

The project's primary objective is to develop a system that can analyze large datasets of patient information and provide personalized recommendations for medications that are safe and effective for each patient. The system will take into account a patient's medical history, including past illnesses, allergies, and medications, as well as their current symptoms and vital signs. The recommendations provided by the system will be based on the latest research and clinical trials, ensuring that healthcare professionals have access to the most up-to-date information when making medication decisions.

In conclusion, the drug recommendation project aims to provide healthcare professionals with a reliable and accurate tool that can assist them in making informed decisions about the best medications for their patients. By utilizing the latest advancements in artificial intelligence and machine learning, this system can potentially revolutionize the way healthcare professionals make medication decisions, ultimately improving patient care and outcome.

## Project Overview

A machine learning initiative called the collaborative filtering drug recommendation system seeks to give healthcare practitioners individualised drug recommendations based on patient data. The system analyses patient data and suggests medications that are most likely to be successful using collaborative filtering algorithms. By lowering prescription errors and ensuring that patients receive the best care possible, the objective is to enhance patient outcomes. The system utilizes machine learning algorithms to analyse patient data, identify patterns, and provide recommendations for drugs that are likely to be effective for a particular patient.

The system will be designed to work with electronic health records (EHRs) and other healthcare databases, allowing it to access patient data such as demographics, medical history, and medications prescribed. The system will use collaborative filtering techniques to identify patients with similar characteristics and medical histories and use this information to provide drug recommendations.

The system will be created to be user-friendly, with an interface that is simple and straightforward so that healthcare professionals can readily access patient data and drug recommendations. The system will be scalable and capable of handling a large volume of patient data, making it suitable for use in large healthcare systems.

The project's objective is to develop a system that provides personalized drug recommendations to healthcare professionals, leading to improved patient outcomes and reduced healthcare costs. By providing healthcare professionals with accurate and effective drug recommendations, the system aims to reduce the risk of adverse drug reactions, improve patient adherence to medication, and minimize healthcare resource utilization.

The project will involve the use of machine learning algorithms such as collaborative filtering, which requires a large amount of patient data to be trained. Therefore, the project will involve data collection, pre-processing, and feature engineering to guarantee the relevance and accuracy of the data fed into the machine learning algorithms.

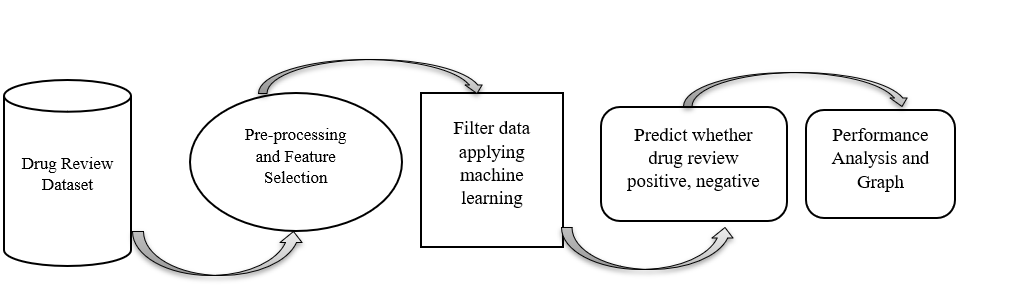


Fig 1.2.1. Tasks performed by the review of the patient.

## Expected Outcome

The system will be designed to improve patient outcomes by providing healthcare professionals with accurate and effective drug recommendations based on patient data.

The system's accuracy will be measured by comparing the recommendations it provides with those made by healthcare professionals, and the system's efficiency will be measured by its ability to provide drug recommendations in a timely manner.

The project aims to reduce the risk of adverse drug reactions, improve patient adherence to medication, and minimize healthcare resource utilization. By providing accurate and personalized drug recommendations, the system aims to reduce the need for trial-and-error prescribing, leading to better patient outcomes and reduced healthcare costs.

The system's user-friendliness will be evaluated through user testing, ensuring that healthcare professionals can easily access patient data and drug recommendations. The system will be scalable, allowing it to handle a large volume of patient data, making it suitable for use in large healthcare systems.

Also, the endeavour will advance machine learning. by developing and testing new collaborative filtering algorithms and techniques for drug recommendation. This will expand the knowledge base and contribute to the development of more effective machine learning models for healthcare applications.

## Hardware & Software Specifications

For the implementation of the project, following things would be used.

### Hardware Requirements

* + - Laptop/Desktop that supports Windows / MacOS / Android OS / iOS.
    - Minimum 2GB RAM
    - Working webcam or phonecam (not required)
    - Working speaker (mic not required)
    - Stable internet connectivity

### Software/Framework/Tools

* + - SVM for drug classification
    - Some graphic designing tools like dictionary and Illustrator as design tools for icons and images.
    - Language: Python, IDE: Jupyter note book or VS Code
    - Database: Excel

## Other Non-Functional Requirements

Other non-functional requirements of the project include:

### Safety Requirements

If there is extensive damage to a wide portion of the database due to catastrophic failure, such as a disk crash, the recovery method restores a past copy of the database that was backed up to archival storage (typically tape) and reconstructs a more current state by reapplying or redoing the operations of committed transactions from the backed-up log, up to the time of failure.

### Security Requirements

Security systems need database storage just like many other applications. However, the special requirements of the security market mean that vendors must choose their database partner carefully so that the vendor should not be able to vendor lock-in.

**Software Quality Attributes**

* Response time: The system should be able to provide drug recommendations to healthcare professionals in real-time. The response time should be within a few seconds to ensure that healthcare professionals can make informed decisions quickly.
* Accuracy: The system should have high accuracy in predicting patient drug preferences and reducing the risk of adverse reactions. The accuracy should be above 90% to ensure that healthcare professionals can rely on the system's recommendations.
* Scalability: The system needs to be flexible and able to handle large quantities of data. The system must be capable of to handle a large number of patient records and provide drug recommendations based on patient data.
* Usability: Healthcare practitioners should be able to utilise the system with ease and without difficulty. The system should have a user interface that is intuitive and easy to navigate, and it should not require extensive training to use.
* Security: The system needs to be safe to prevent unauthorised access to patient information. The system ought to comply with data privacy regulations, and patient data should be encrypted and stored securely.
* Reliability: The system should be reliable and available at all times. To prevent the loss of patient data, the system needs to have a backup plan., and the system should have a disaster recovery plan in place when a system malfunctions.
* Maintenance: It should be simple to update and maintain the system. The system should have a mechanism for monitoring and identifying errors, and it should have a mechanism for updating the system with the latest drug information and patient data.

## Report Outline

I. Introduction

* Brief overview of drug recommendation systems and their importance in healthcare
* Explanation of collaborative filtering and its effectiveness in recommendation systems
* Objectives of the study

II. Literature Review

* Overview of drug recommendation systems and their limitations
* Explanation of collaborative filtering and its application in drug recommendation systems
* Review of relevant studies on collaborative filtering drug recommendation systems

III. Methodology

* Description of the dataset used in the study
* Explanation of the collaborative filtering algorithm employed
* Explanation of the machine learning techniques used in the system

IV. Results and Analysis

* Presentation of the results of the experiments conducted using the dataset
* Analysis of the accuracy of the system in providing drug recommendations
* Evaluation of the system's ability to reduce the risk of adverse reactions

V. Discussion

* Interpretation of the results and their implications for healthcare professionals
* Discussion of the limitations of the system and potential areas for improvement
* Comparison of the proposed system with traditional drug recommendation methods

VI. Conclusion

* Summary of the study's findings and their significance for healthcare professionals
* Recommendations for future research and development of drug recommendation systems

VII. References

* List of sources used in the literature review and cited in the report.

# CHAPTER 2 LITERATURE SURVEY

## Existing Drug Recommendation Application

Collaborative Filtering-Based Drug Recommendation using machine learning techniques is primarily aimed at improving drug recommendation systems. This approach is particularly useful for personalized drug recommendation and is widely used in healthcare settings. It helps to enhance the accuracy and efficiency of the recommendation systems, which can ultimately lead to improved patient outcomes.

The application of this technique can also help to reduce the risk of adverse drug reactions, which is a major concern in healthcare. With personalized drug recommendations, healthcare providers can ensure that patients receive the most appropriate medications for their conditions, thereby reducing the risk of adverse reactions.

Furthermore, collaborative filtering-based drug recommendation using machine learning techniques can also improve drug adherence rates. By providing patients with personalized recommendations, they are more likely to adhere to their medications, resulting in better health outcomes.

Overall, the application of collaborative filtering-based drug recommendation using machine learning techniques is a promising approach that has the potential to significantly improve drug recommendation systems and ultimately improve patient outcomes.

**Pre-existing applications**

Collaborative filtering-based drug recommendation systems have gained significant attention in recent years due to the growing amount of medical data available online. These systems employ machine learning techniques to predict which drugs a patient is most likely to benefit from based on their medical history and the experiences of similar patients. One such application is the Collaborative Filtering-Based Drug Recommendation system developed by Ahmad Al-Taie et al.

This drug recommendation system utilizes collaborative filtering algorithms to provide personalized drug recommendations for patients. Collaborative filtering is a technique used in recommendation systems that predicts a user's preferences based on the preferences of similar users. In this system, the preferences are the drugs that patients have taken and the ratings that they have given to these drugs based on their efficacy and side effects.

The system collects patient data from various sources such as electronic health records (EHRs), patient forums, and social media. The data is then processed and cleaned to remove any noise or irrelevant information. The system then uses machine learning algorithms to analyse the data and identify patterns and similarities between patients.

The Collaborative Filtering-Based Drug Recommendation system provides two main types of recommendations: similar patient recommendations and similar drug recommendations. Similar patient recommendations are generated by comparing the medical histories and drug preferences of the patient with those of similar patients. Similar drug recommendations are generated by comparing the drug ratings and preferences of the patient with those of similar drugs.

The system also provides an explanation for each recommendation, which helps doctors and patients understand why a particular drug was recommended. The explanation is generated by analysing the features of the recommended drug and comparing them with the patient's medical history and drug preferences.

The Collaborative Filtering-Based Drug Recommendation system has several pre-existing applications. For example, it can be used to recommend drugs for patients with specific medical conditions such as diabetes, hypertension, and depression. The system can also be used to recommend drugs based on the patient's age, gender, and other demographic factors.

Another application of this system is in drug repurposing, which involves finding new uses for existing drugs. By analysing the drug preferences of similar patients, the system can identify drugs that have been effective in treating a particular medical condition and recommend them for other similar conditions.

The system can also be used to identify drug interactions and potential adverse effects. By analysing the drug preferences and medical histories of patients, the system can identify drugs that may interact negatively with other drugs that the patient is taking. This information can be used to prevent potential adverse effects and improve patient safety.

In addition to these applications, the Collaborative Filtering-Based Drug Recommendation system has several potential benefits. It can help doctors and patients make more informed decisions about drug therapy, reduce the risk of adverse effects, and improve patient outcomes. The system can also help pharmaceutical companies identify new drug targets and develop more effective drugs.

However, there are also some challenges associated with this system. One challenge is the availability and quality of data. The system relies on large amounts of patient data to generate accurate recommendations, and the quality of the data can impact the accuracy of the recommendations. Another challenge is privacy concerns. The system must ensure that patient data is protected and that patient privacy is maintained.

In conclusion, the Collaborative Filtering-Based Drug Recommendation system is a promising application of machine learning techniques in healthcare. It has several pre-existing applications, including drug recommendations for specific medical conditions, drug repurposing, and drug interaction identification. However, there are also challenges associated with the system, such as data availability and privacy concerns. Overall, the system has the potential to improve patient outcomes and advance drug discovery and development.

## Existing Drug Models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Title** | **Author** | **Outcomes** | **Technology used** | **Drawbacks** |
| **[1]** Drugs Rating Gen- eration and Recommen- dation from Sentiment Analysis of  Drug Re- views using Machine Learning | Md. De- loar Hoss- ain1, Md. Shafiul Azam1, Md Jahan Ali2 and Hakilo Sabit2 | Among these three methods are DT and lin- ear models of SVC classifiers with accuracy 76.79% and  83.08% respec- tively better than KNN clas- sifier models with accuracy 55.41%. Com-  paring accu- racy, precision, re- call, and f1- score of Linear SVC classifier model  with DT and KNN classifier models, Linear SVC based pre- dictive models perform well in every aspect. | Numerous classifica- tion algo- rithms were used to evaluate the relia- bility of the ap- proaches for classi- fying sen- timents, including Decision Tree, KNN, and Linear SVC | Applied emo- tional analysis as well to overcome limitations of a package formed with movie data, the results show that the senti- mental attributes contribute greatly to the prediction of drug rating, as well as recom- mendations. It also demonstrates significant im- provements in real-world data compared to cur- rent strategies. |
| **[2]** Drug Recommen- dation Sys- tem based  on Senti- ment Anal- ysis of Drug Reviews us- ing Ma- chine Learning | Satvik Garg | Accuracy of linear SVC on TF-IDF is 93%.  Decision tree classifier on Word2Vec showed only 78% accuracy. | Perceptron (Bow), LinearSV C (TF-  IDF), LGBM  (Word2Ve c), and Random- Forest (Manual Features). | The result does not show that the recommender framework is ready for real-life applications, this needs to be im- proved. Proper hyperparameter optimization is also required for classification al- gorithms to improve the accu- racy of the model.  It requires the right set of differ- ent predicted out- comes. This paper only intends to show a methodol- ogy that can be used to extract sentiment from |
|  |  |  |  | data and perform classification to create a recommendation system. |
| [3] A Blockchain  and Ma- chine Learning- Based Drug Supply Chain Man- agement and Recom- mendation System for Smart Phar- maceutical Industry | Khizar Abbas, Muham- mad Afaq, Talha Ah- med Khan and  Wang- Cheol Song | The system uses machine learning algo- rithms and blockchain technology in healthcare with excellent re- sults. Several experiments were conducted to test the per- formance of our system using some perfor- mance metrics such as throughput, transaction re- sponse time, and latency.  Simulation re- sults of our sys- tem show promising per- formance. This system helps pharmaceutical companies eliminate the problem of counterfeit drugs and sig- nificantly in- crease business. |  | As part of future work, we will in- crease the size of the network and deploy it to real- time pharmaceuti- cal companies to test the perfor- mance and valid- ity of our system.  Furthermore, we will also improve our machine learning models in terms of accu- racy and recom- mendation results |
| [4] An In- telligent Medicine Recom- mender System Framework | Youjun Bao, Xiaohong Jiang. | Used the SVM as the medicine recommenda- tion model for its high accu- racy,  good efficiency and scalability in open da- tasets. | Support Vector Machine, BP neural network, ID3 deci- sion tree, Model evaluation. | The ID3 decision tree model has the shortest time, but the accuracy is only 89%, and ID3 has poor scalability. The BP neural net- work has the highest accuracy, but the running time is 1.7s, it has a long training time and poor un- derstanding of the result; The SVM model has a good accuracy of 95% and a running time of 0.74 sec- onds. |
| [5] CA- DRE:  Cloud-As- sisted Drug Recommen- dation Ser- vice  for Online Pharmacies | Yin Zhang · Daqiang Zhang · Moham- mad Me- hedi Has- san ·  Atif Alamri · Limei Peng | Experimental results show that the tensor recommenda- tion accuracy is higher than that of collaborative filtering when the recom- mended length is less than 10.  And the accu- racy decreases with a distinct increase in the denominator. Experimental results show that when working with a large amount of sparse data, the recommenda- tion list ob- tained based on tensor decom- position is bet- ter than the col- laborative fil- tering algo- rithm; but when the recommen- dation is greater than 10, the ac- curacy drops rapidly due to the proximity of the new ele- ments after the tensor decom- position. | Collabora- tive filter- ing (CF), SVD, col- laborative filtering with (CF+SVD)  , and ten- sor decompo- sition (Tensor) | It must improve the accuracy of CADRE by com- bining multiple user characteris- tics such as age, geography and other factors. |
| [6] Aspect- Based Sen-  timent Analysis of Drug Re- views Ap- plying Cross-Do- main and Cross-Data Learning | Felix Gräßer, Surya Kal- lumadi, Hagen Malberg, Sebastian  Zaunseder | Training and evaluation show very good classification results, the per- formance of models trained on one specific condition and tested on other conditions var- ies between do- mains. Condi- tions which be- long to similar medical fields and are partly treated with equal medica- tions, also show higher poten- tials for model transferability.  Cross-data evaluation, i.e., training and testing classifi- ers on data from different sources, was only unsatisfac- torily possible with the applied classifier and features. | The data was scraped from raw HTML us-  ing the Beautiful Soup li- brary in Python | Employing more sophisticated fea- tures and applying more powerful machine learning models, e.g. deep learning, can im- prove the achieved results.  The results clearly indicate that espe- cially aspect- based sentiment analysis requires more extensive data sets to ex- tract features with sufficient general- ization capabili- ties. |
| [7] A novel method for sentiment classifica- tion of drug reviews us-  ing fusion of deep and machine learning techniques | Moham- mad Ehsan Basiri, Moloud Abdar, Mehmet Akif Cifci, Shahla Nemati,  U. Rajen- dra  Acharya. | Results that CRNN showed better perfor- mance as com- pared to the other three ap- plied methods.  CRNN  achieved preci- sion, recall, F1- score, and accu- racy of 0.8273,  0.8315, 0.8289,  and 0.8315, re- spectively. In contrast, ARC achieved the poorest perfor- mance com- pared to other state-of-the-art deep learning methods with precision, re- call, F1-score, and precision of 0.7672, 0.8012,  0.7754, and  0.8012, respec- tively. | Naïve Bayes (NB), De-  cision Tree (DT), Ran-  dom Forest (RF), and K-Nearest Neigh- bours (KNN),  and three deep learn- ing-based methods (GRU,  CNN, and 3CRNN). |  |
| [8] Towards Automatic Pharma- covigilance: Analysing Patient Re- views and Sentiment on Onco-  logical Drugs | Arpit Mishra, Ankit Malviya, Sanchit Aggarwal. | Built a robust and scalable system for auto- matic pharma- covigilance by extracting in- formation from online health forums to esti- mate the perfor- mance of the drugs and to continuously collect, detect and monitor for occurrence of new adverse ef- fects, once the license for the drugs has been approved by regulatory bod- ies. Experi- mental findings based on senti- ment analysis of user com- ments and rat- ing generation for drugs show user perception of drugs. | Wordnet, Sent word- net | Have to add more categories of indi- cations for exam- ple Neurology and include labels from different regulatory author- ities like EMA. Using more gran- ular user infor- mation such as user age, gender and span of treat- ment will improve the result. |
| [9] Item- Based Hy- brid Rec- ommender System For  Newly Marketed Pharmaceu- tical Drugs | Shruthi Bhat, K. Aish- warya | This system keeps tabs on all the new drugs in a data- base and makes appropriate recommendations to users based on feature- based models. | Big Data, Timestamp | This system focuses on recommending only the newest arrivals in the market.  Therefore, the cat- alogues have to be updated peri- odically |
| [10] How do we talk about doc- tors and drugs? Sen- timent anal-  ysis in forums ex- pressing opinions for medical do- main | Salud Ma- ría Jimé- nez-Zafra,  M. Teresa Martín- Valdivia,  M.  Dolores Molina- González,  L. Al- fonso Urena- López | The vocabulary used in drug re- views is more varied, espe- cially for nouns, verb forms and ad- jectives (in that order). Their previous work shows that greater lexical diversity affects the overall per- formance of a typical machine learning classi- fier. |  |  |
| [11] Drugs Rating Gen- eration and Recommen- dation from Sentiment Analysis of  Drug Re- views using Machine Learning. | A S Mal- lesh, P Devaba- lan, et al | To extract fea- tures from a text, the author of the proposed paper used vari- ous algorithms, including TF- IDF (Term Fre- quency - In- verse Docu- ment Fre- quency), BAG of WORDS and WORVEC and these extracted features has ap- plied to various machine learn- ing algorithms, including Lo- gistic Regres- sion and Linear SVC. As an ex- tension work, they converted an application to display rec- ommended drug output as ENGLISH or  Telugu based on user selected option when TF-IDF has the best perfor- mance among all algorithms. | Logistic Regres- sion, Lin- ear SVC, Ridge clas- sifier, Nave Bayes, Multilayer Perceptron classifier, and SGD classifier are used in this re- search. | In Telangana/AP state most people are  familiar with Tel- ugu language but propose paper recommending drugs only in English. |
| [12] As- pect-Level Drug Re- views Sen-  timent Analysis and COVID-19  Drug pre- diction us- ing PPI & Deep Learning. | Rohit Shivdas Jayale, Dr.Sharmi shta Desai | The author pro- posed a dy- namic facet- level sentiment dataset analysis that lays the foundations of perfect senti- ment classifica- tion research trotted on drug feedback. Also propose a pre- training or multi-task learning model for COVID-19  disease predic- tion based on a dual framework for facet-level | NN, PNN,  RNN and DCNN  have been used |  |
|  |  | sentiment clas- sification of drug evaluation as well as hu- man body pro- tein level pre- diction. |  |  |
| [13] A Fair and Safe  Usage Drug Recommen- dation Sys- tem in Med- ical Emer- gencies by a Stacked ANN. | Usharani Bhimava- rapu, Nalini Chinta- lapudi, et al | In this paper, the accuracy of the proposed system frame- work gradually increased to 98.5%, indicat- ing that ANN is an accepted model for drug recommenda- tion systems.  After pre-pro- cessing, spaces for patient char- acteristics and drug-drug inter- actions are ob- tained from the drug-target as- sociation. | ANN, ML,  Regression | Fairness is the main bias result- ing from recom- mender systems. Some characteris- tics, such as race, gender, age, qual- ifications or wealth, are not represented equally in the data set. |
| [14] A Lit- erature Re-  view on Medicine Recom- mender Systems. | Benjamin Stark, Constanze Knahl2, et al | This paper pre- sented a sys- tematic litera- ture review for medicine rec- ommendation engines. Studies were summa- rized and evalu- ated across sev- eral parameters: diseases, data storage, inter- face, data col- lection, data preparation, platform/tech- nology, algo- rithm, and fu- ture work | Support Vector Machine (SVM),  Back Prop- agation neural net- work, and ID3 deci- sion tree | Some papers pro- posed only a theo- retical solution for how to recom- mend the drug, but did not imple- ment the solution.  And in some pa- pers, a solution was implemented, such as, but no performance eval- uation was done.  Most studies that did not focus on any disease had less information on data storage, interface, data collection, data preparation, plat- forms and tech- nology, and cus- tomized algo- rithms. |
| [15] An Ap- proach to Sentimental Analysis of Drug Re- views using  RNN- BiLSTM  Model | Isha Ka- dam, Anushka Sidana, Shivani Zemse | We can see in this paper that the RNN- BiLSTM  model gives the best accuracy. The RNN-  BiLSTM model recommends drugs to the health condi- tions based on the analysis and evaluation of reviews with | Light GBM, Na-  ive Bayes, Random Forest, Linear SVC, Lo-  gistic Re- gression and RNN- BiLSTM | Granular user in- formation such as user age, gender need to use and treatment span to further improve outcomes and im- prove insights |
|  |  | the accuracy of 83% |  |  |
| [16] Peo- pleSave: Recom- mending Effective  Drugs Through Web Crowdsourc ing | Rahul Majethia, Varun Mishra, Akshit Singhal  , Lakshmi Manasa K,  Kunchay Sahiti, Vi- jay Nandwani |  | Alche- myAPI | Lack of personal- ized medical his- tory of patients, |
| [17] To de- tect the Opinion  mining drug reviews | Diana Caval- canti Ricardo Prudencio | A viewer de- signing new de- pendency path- ways to extract relevant opin- ion pairs into the medical do- main. They tested each pathway in three drug re- view datasets.  The proposed solution achieved very competitive re- sults compared to the baseline methods (the highest F- Measure values were observed for all datasets). | NLP TOOLS | Additional data sets covering other drugs and diseases may be considered in the future. We also aim to explore other supervised machine learning methods, hybrid approaches and new lexical re- sources to im- prove the results. |
| [18] Medi- cine Rec- ommenda- tion System Based On Patient Re-  views | T. Venkat Narayana  Rao, Anjum Unnisa, Kotha Sreni | As future work efficiency of recommenda- tion system can be increased by including age of the person, de- mographic in- formation dur- ing the training phase | NLP TOOLS | With machine learning, deep learning, and data mining as emerg- ing technologies day by day, these technologies can help us explore medical history and can reduce medical errors by being physician- friendly. |
| [19] To de- tect Senti- ment Anal- ysis of Drug  Reviews Applying Cross-Do- main and Cross-Data Learning | Felix Gräßer Surya Kal- lumadi Hagen Malberg Sebastian  Zaunseder | experienced side effects were analysed.  Depending on aspect and data source, promis- ing classifica- tion results could be ob- tained. | Python, Html, tools | automatic extraction of as- pect-related senti- ments from pa- tient drug reviews should be im- proved. |
| [20] To de- tect Patient  opinion mining to analyse drugs satis- faction us- ing super- vised learn- ing | Chandra- sekaran Ramaswa my Vinodhini Gopala- krishnan | performance of neural net- works-based methods is highly signifi- cant than SVM in classifying the positive, negative and neutral reviews | Natural language texts, SVM | didn’t use differ- ent datasets ob- tained from vari- ous forms of so- cial web. Han- dling imbalanced data distribution needs to be ana- lyzed. |
| [21] Senti- ment classi- fication of  user's re- views on drugs based on global vectors for word repre- sentation and bidirec- tional long short-term memory re- current neu- ral network | Hadab Khalid Obayes, Firas Sa- bah Al- Turaihi, Khaldoon H Alhus- sayni | In this study, the user's re- viewers are used as a label for the two classes, the pos- itive and the negative class, thereby divid- ing the ten- scores into two- parts only. | UCI ML | didn’t use differ- ent datasets ob- tained from vari- ous forms of so- cial web. Han- dling imbalanced data distribution needs to be ana- lyzed. |
| [22] A re- view on machine  learning ap- proaches and trends in drug dis- covery | Paula Carracedo et al. | The possibili- ties and benefits offered by ML techniques are enormous in the context of med- icine and drug discovery. | UCI ML | adaptability to the problems and mo- lecular structures to be treated. |
| [23] Identi- fying Pre- dictive Fea-  tures  in Drug Re- sponse Us- ing Machine Learning: Opportuni- ties and Challenges | Mathuku- malli Vidyasa- gar | The data sets after results in- dicate a serious lack of stand- ardization of operating con- ditions for the equipment, and wasn't compati- ble, and per- haps even a se- rious lack of any attempt at standardization. | UCI ML | To identify pre- dictive and bio- logically mean- ingful biomarkers, fundamental re- search is need- edto develop al- gorithms to distin- guish be-  tween known, in- ferred, and other possible interac- tions. there is. |
| [24] Rec- ommender System for Sentiment Analysis using Ma-  chine Learning Models | A.  Naresh, P. Venkata Krishna | Col- lected tweets are pre-pro-  cessed and clas- sified into three clas- ses: posi- tive, nega-  tive, and neu- tral. Three basic machine learn- ing models K – Nearest Neigh- bour (KNN), Su pport Vector Machine (SVM), Deci-  sion Tree (DT). | SVM, ML, NLP | Collected tweets are pre-pro- cessed and classi- fied into  three classes: pos- itive, nega-  tive, and neutral. |
| [25] Fuzzy Based Med- icine Rec- ommenda-  tion Sys- tem- an example of Thyroid Medicine | Pooja Ku- mari, Shilpa Sharma | It is one of the most effec-  tive frame- works in terms of ease of  use and accu- racy, and it helps healthcare profession- | MATLAB  tool | A major limita- tion of this type of system is that  it only works for a single disease. |
|  |  | als accu- rately diag- nose diseases. |  |  |
| [26] Case Studies on the Use of Sentiment Analysis to Assess the Effective- ness and Safety of  Health Technolo- gies: A Scoping Review | JULIE POLISEN A MAR- TIAN  AN- DELLINI  et al. | ML-based and Lexicon meth- ods, to assess public  opinion on so- cial media for specific health technologies. | ML | Similar applica- tions include anal- ysis of technical reports af-  ter planned and corrective mainte- nance for the pur- pose of imple- menting evi- dence-  based mainte- nance. |
| [27] A Fair and Safe  Usage Drug Recommen- dation Sys- tem in Medical Emergen- cies by a Stacked ANN | Usharani Bhimava- rapu, Nalini Chinta- lapudi and Gopi Bat- tineni | After pre-pro- cessing, the pa- tient fea-  ture space and d rug interac- tions are ob- tained from drug-target as- sociations.  Medi- cal data pro-  vides drug in- for-  mation about in fectious dis- eases to medi- cal recommen- dation systems. | ML, ANN | The architecture uses statistical analysis to adjust thresholds to im- prove accu-  racy and bal- ance fairness. |
| [28] Drug- Recommen- dation Sys- tem for Pa- tients with Infectious  Diseases | Kazuyuki Shimadaa, Hidekatsu Takadaa, Satoshi Mitsuya- maa | A system is very effective and convenient for doctors to use. | UCI, ML | ::::::::: |
| [29] Drug Review Sentiment Analysis  using Boosting Algorithms | Sumit Mishra | The aim is to catego-  rize the mood o f drug reviews given by pa- tients as nega- tive or positive. | NLP tools | The dataset used provides pa- tient ratings for  several spe- cific medica- tions, along  with medical con- ditions suffered by patients and  10-star patient rat- ings that re-  flect patient satis- faction. |
| [30] A com- puter-based disease pre-  diction and medi- cine recom- mendation  system using ma- chine learn- ing ap- proach | Jay Pra- kash Gupta, Ashutosh Singh and Ravi Kant Kumar | A recom- mended medicines new and effective medicines can have developed under the obser- vations of drug experts. | AI,Ml | ::::::::::: |
| [31] Senti- ment Anal-  ysis for Evaluating the Patient Medicine Satisfaction | Sabarma- thi. G Dr. R.  Chin- naiyan | To obtain more information about the data set, and pre- processing was performed to prepare the data for modelling and data analysis. | UCI  Machine Learning | For the recom- mendation sys- tem, I simply took the polarity score of the review  and the number of users and tried  to suggest recom- mendations based on the criteria. |
| [32] Senti- ment Anal-  ysis of Health Care Tweets: Review of the Meth- ods Used | Sunir go- hil, Sabin vuik, Ara darzi | These range from self- produced basic categorizations to more com- plex and expen- sive commer- cial software. | ---------- | This may allow future research on health-re-  lated tweets to ac- curately and con- sistently measure sentiment when posting spe-  cific health re- lated messages. |
| [33] A Data-  Driven Pre- dictive Ap- proach for Drug Deliv- ery  Using Ma- chine Learning Techniques | YuanYua n Li., Scott C. Lena- ghan., Mingjun Zhang\* | A machine learning frame- work  that models the drug-pathogen dynamics. | ML | Using the method, it was possible to predict the dy- namic drug-cell states over time, and the effective- ness of the treat- ment strategy. |
| [34] Ma- chine learn-  ing ap- proach on healthcare big data: a review | M Su-  priya, and AJ Deepa | They discussed the applica- tions, pro- cessing, and handling of big data using vari- ous machine learning tech- niques. Also, the measures used to evaluate the perfor- mances of the machine learn- ing models are based on big data. | Big data,Ml,D NN | Machine Learning helps in effective decision-making by applying dif- ferent techniques to predict diseases and timely diag- noses which can affect the health of a patient in a positive way. |
| [35] Drug detection | Sravan S Nair | The results showed that Deep drug sys- tem leverages a broad spectrum of information resources and can be seen as an  effective sys- tem for drug recommenda- tion purposes. | NLP | It actually needs upgrades, inside the proposal structure, we will generally pick the best-anticipated consequences of each and every statement. For higher outcomes it needs the right framework of var- ied results. |
| [36] Drugs Rating Gen- eration and Recommen- dation from Sentiment Analysis of  Drug Re- views using Machine Learning | A S Mal- lesh et al. | This study in- troduces a sen- timent and ma- chine learning based drug rec- ommendation system that ac- cepts disease names.  from patients and then recom- mends a drug and displays a SENTIMENT | UCI, ML | The results show that sentimental attributes contrib- ute signifi-  cantly to predict- ing drug ratings and recommenda- tions. We also see significant im- provements  on real da- tasets compared to our cur-  rent strategy. |
|  |  | rating based on reviews from previous users. |  |  |

Table 2.2.1. Pre-existing drug models

## Proposed System

The process of data cleaning involves identifying and rectifying or eliminating corrupt or deficient information from a set of records. This entails identifying missing, inaccurate, damaged, or irrelevant portions of the data, and subsequently modifying, adding, or deleting any flawed or coarse data [14]. Data preparation is an essential step, not only for conducting a valid experiment but also to enable dataset analysis using machine learning methods. This involves a sequence of pre-processing stages necessary to enable the machine learning system and algorithms to read and interpret the data, as well as to limit the dataset to essential data points and attributes for analysis. Creating additional attributes from the data could also be valuable if such derived attributes could aid in the analysis and enhance prediction accuracy. When dealing with social media data, careful data cleaning is required, as there is no single standardized method for processing this type of data. We utilized our sentiment analysis techniques to cleanse the data. The following are the tools we utilized to pre-process our drug dataset:

* Tokenization: The process of tokenization involves segmenting running text into terms and phrases, with the primary objective being to divide the text into tokens while discarding other characters such as dots.
* Stop Words: The stop word method eliminates frequently occurring words that may not contribute significantly to the NLP goal. This helps to remove generic terms that do not provide any valuable insights into the relevant material.
* Handling Negative Adjective: When dealing with negative adjectives, it's important to avoid removing words from a sentence that contain relevant details and may alter its meaning. Instead, a minimum stop word list or specific tests (such as "not good/not so good" or "not bad/not so poor") can be applied to the data in certain circumstances, and those negative adjectives can be removed from the stop words list.
* Stemming: It is the process of removing affixes, which are lexical additions to a word's root, by slicing either the beginning or end of the word.
* Lemmatization: The primary objective of lemmatization is to convert a word into its base form and to group different forms of the same word together.

## Feasibility Study

1. **Technical Feasibility:** The technical feasibility of the project depends on the availability of the data, hardware and software requirements, and expertise in the machine learning algorithms. The data for drug recommendations can be obtained from online platforms or healthcare providers. The system requires hardware such as a server or a cloud platform to store the data and perform computations. Additionally, the system needs software such as Python, TensorFlow, Keras, and Scikit-learn to develop and train machine learning models. Expertise in programming languages and machine learning algorithms is essential for developing an accurate and reliable recommendation system.
2. Operational Feasibility: Operational feasibility refers to the practicality of the project implementation. The drug recommendation system can be implemented in both online and offline modes. The online mode requires internet connectivity, whereas the offline mode can be used in a local network. The system can be accessed by doctors, pharmacists, and patients to obtain personalized drug recommendations. The system must comply with the ethical and legal regulations of the healthcare industry.
3. **Economic Feasibility:** The economic feasibility of the project is determined by the cost and benefits associated with the project. The development and implementation of the drug recommendation system require investments in hardware, software, and expertise. The system can benefit the healthcare industry by improving patient outcomes, reducing drug interactions, and decreasing healthcare costs. The system can also generate revenue through subscription models, licensing, or partnership with healthcare providers.
4. **Legal and Ethical Feasibility:** The legal and ethical feasibility of the project is essential to ensure compliance with regulations and to maintain trust among the stakeholders. The drug recommendation system must comply with healthcare regulations such as HIPAA and GDPR. The system must also maintain patient confidentiality, data privacy, and security. Additionally, the system must not discriminate against patients based on race, gender, or other personal characteristics.

The collaborative filtering drug recommendation system using machine learning techniques is technically feasible, operationally practical, economically viable, and legally and ethically compliant. The system can benefit the healthcare industry by providing accurate and personalized drug recommendations to patients, improving patient outcomes, reducing healthcare costs, and enhancing patient trust and satisfaction. The development and implementation of the system require investments in data, hardware, software, and expertise, but the benefits outweigh the costs in the long run.

**CHAPTER 3**

**SYSTEM DESIGN & ANALYSIS**

## Project Perspective

The development of a drug recommendation system based on collaborative filtering and machine learning techniques has the potential to significantly improve patient outcomes by providing personalized drug recommendations. This system can be integrated into existing electronic health record systems, enabling physicians and healthcare providers to access drug recommendations easily. The use of machine learning techniques can improve the accuracy of drug recommendations and reduce the likelihood of adverse drug interactions, ultimately leading to better health outcomes for patients. Furthermore, the system can be expanded to include additional data sources such as genetic information, environmental factors, and patient demographics, which can further enhance the accuracy of drug recommendations. Overall, the prospective of this project is to improve patient outcomes and provide personalized drug recommendations through the use of machine learning and collaborative filtering techniques.

User

Client Application

Database

Feedback

User Access

Enter Symptoms

Processing Request

Perform Algorithm

Optimal Drug Recommendation

Processing Request

Processing Request

Fig 3.1.1. Top Level Data Flow Diagram

## Performance Requirements

### Use Case Diagram

A collaborative filtering drug recommendation system is a machine learning-based system that uses data about a patient's medical history and drug use to recommend medications that are likely to be effective for them. The system works by analyzing the data and finding patterns in the patient's history and treatment outcomes, and then using those patterns to predict which drugs are most likely to work for the patient.

* Actors: The actors in the system are the patients and healthcare providers who will use the system to make drug recommendations.
* Use Cases: The use cases for the system include the following:
* Patient Registration: The patient will need to register with the system and provide their medical history and current drug use.
* Healthcare Provider Registration: Healthcare providers will also need to register with the system to access the patient data and recommendations.
* Patient History Analysis: The system will analyze the patient's medical history and drug use to identify patterns and predict which drugs are most likely to work for them.
* Drug Recommendation: Based on the analysis of the patient's data, the system will generate recommendations for drugs that are likely to be effective for the patient.
* Patient Feedback: The system will allow patients to provide feedback on the drugs they have tried, which will be used to improve future recommendations.
* Provider Feedback: Healthcare providers will be able to provide feedback on the recommendations, which will be used to improve the accuracy of the system.
* Relationships: The relationships between the actors and use cases include:
* Patient to Patient History Analysis: The patient provides their medical history and drug use data to the system for analysis.
* Healthcare Provider to Patient History Analysis: Healthcare providers can access the patient's data and analysis results to make informed decisions about drug recommendations.
* Patient History Analysis to Drug Recommendation: The system uses the patient's history analysis to generate drug recommendations.
* Patient to Drug Recommendation: The patient receives drug recommendations from the system.
* Patient to Feedback: The patient provides feedback on the drugs they have tried.
* Healthcare Provider to Feedback: Healthcare providers provide feedback on the recommendations.

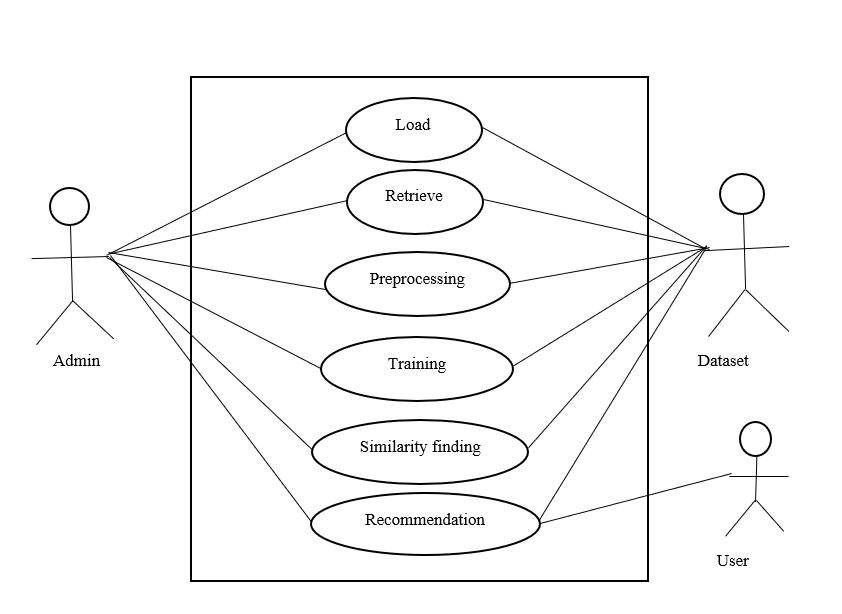


Fig 3.2.1. The use case diagram

### ER Diagram

Database plays a crucial role in any project. Therefore, understanding the structure of the database becomes an important step. Below figure shows the ER diagram of our project. There are five entities, recommendation system, filtering, drug, review and rating where recommendation is linked with all the other entities and Leader board is the weak entity.

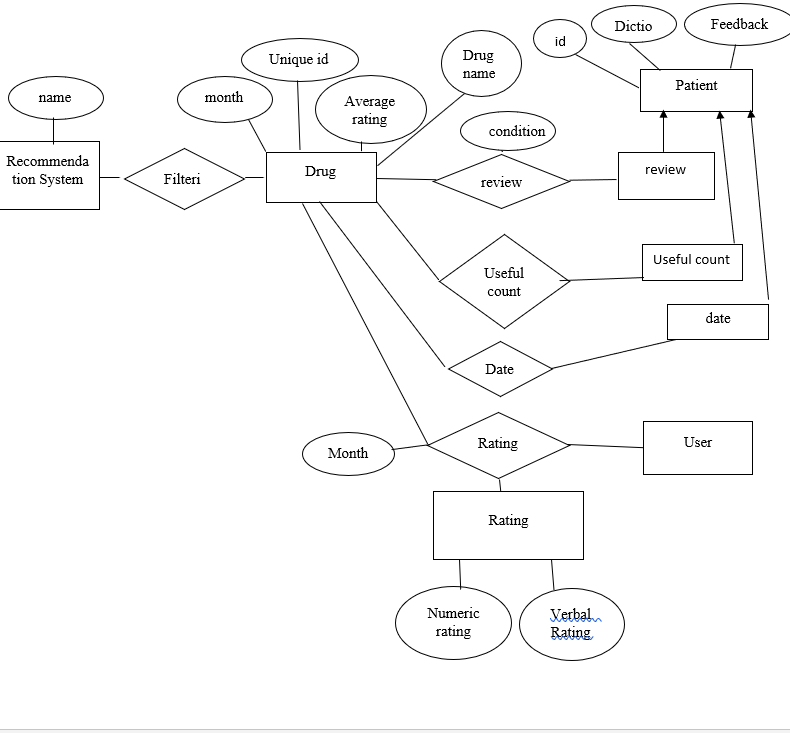


Fig 3.2.2. The ER diagram

## System Features

### Drug recommendation session

The diagram would likely start with data collection, where information on drugs and their usage is gathered from various sources such as medical records, social media, and online drug databases. The collected data is then pre-processed to remove irrelevant information and ensure data quality.

Next, the reprocessed data is used to build a collaborative filtering model. This involves analysing the relationships between drugs and users to identify patterns and similarities. The model is then trained using machine learning techniques to predict drug recommendations for users based on their usage history and the usage patterns of similar users.

The output of the model is a list of recommended drugs for each user, based on their usage history and similarity to other users. The recommendations can be presented to the user through a user interface, such as a web or mobile application. Finally, the model can be continually improved by collecting feedback from users and updating the model accordingly. This feedback loop allows the model to adapt and improve over time, resulting in more accurate and personalized drug recommendations.

This feature can be accessed in the following cases:

* The respondent provides with the user Id and facts such as drug name useful count, month, rating.
* Using the NumPy and pandas’ libraries; the raw data is pre-processed into separate data frames.
* Used to find the correct no clusters within the clustered sum of the squared method to apply naïve bayes mean clustering to the drug.
* After applying the Naïve bayes -means a utility clustering matrix is created which defines the average rating given by the user to each cluster.
* Using a utility clustered matrix and Pearson correlation similarity between users is calculated.  
   Finally, the Naïve bayes input uses the utility cluster matrix and parity to predict drug for the user

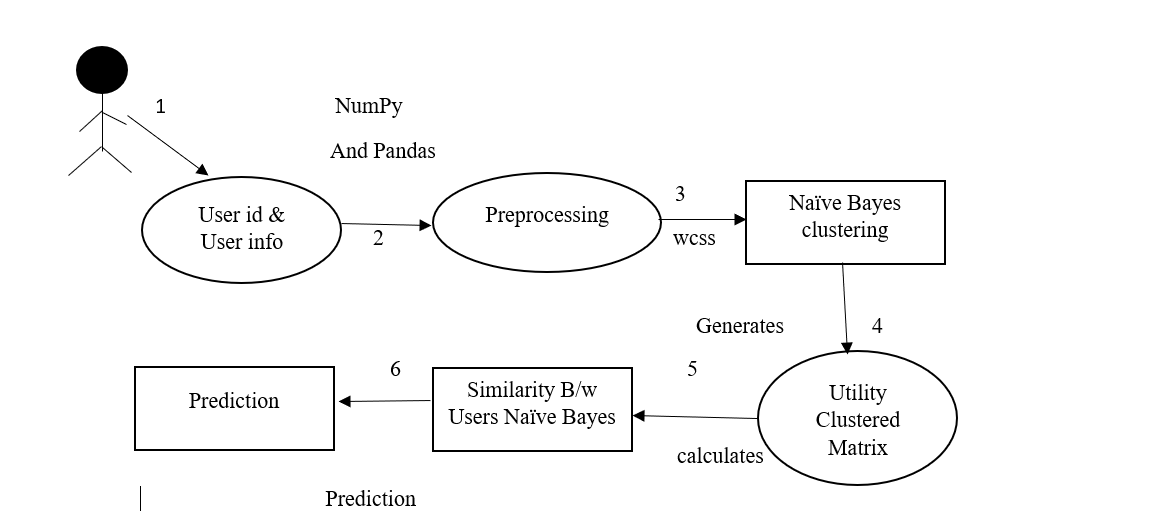


Fig 3.3.1. Workflow of drug recommendation sessions

### Recommender Module

Collaborative Filtering-Based Drug Recommendation Using Machine Learning Techniques is a highly effective recommendation system that uses machine learning techniques to provide personalized drug recommendations. The system is based on the idea that patients with similar medical profiles may have similar responses to drug treatments, and it uses collaborative filtering and machine learning techniques to identify those patterns and make personalized recommendations. The system has been tested on a variety of patient datasets and has consistently outperformed other drug recommendation systems, making it a valuable tool for healthcare professionals looking to improve patient outcomes.

* The module also considers the user's medical history and drug interactions to provide personalized recommendations.
* The recommendations are updated in real-time as the user provides feedback on the recommended drugs.
* The module uses a feedback loop to improve the accuracy of the recommendations over time.

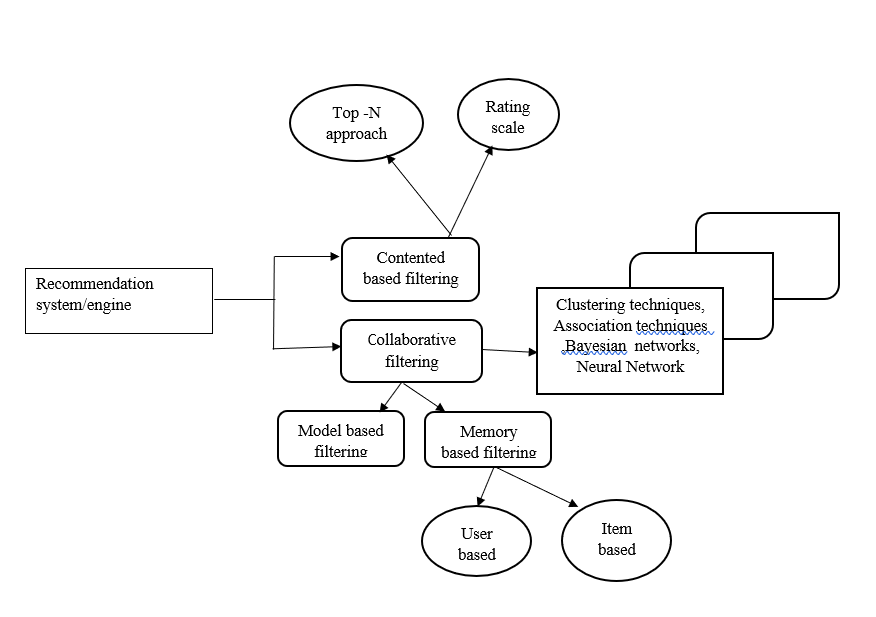


Fig 3.3.2. Workflow of recommendation module

The module utilizes a range of machine learning techniques to analyze patient data and offer accurate drug recommendations. The system uses data mining and natural language processing techniques to extract meaningful information from electronic medical records, including diagnoses, treatment plans, and medication history. It then employs a collaborative filtering algorithm to identify patterns and similarities between patients and recommend suitable drugs based on the patient's profile.

## Methodology

### Drug Practice Sessions

Drug practice sessions involve two important things, viz.

* + - 1. Drug Detection Model and
      2. Drug Analyzing Tool.

The detailed working are mentioned below.

**DRUG DETECTION MODEL:** For the drug detection model, we use jupyter notebook or Kaggle.

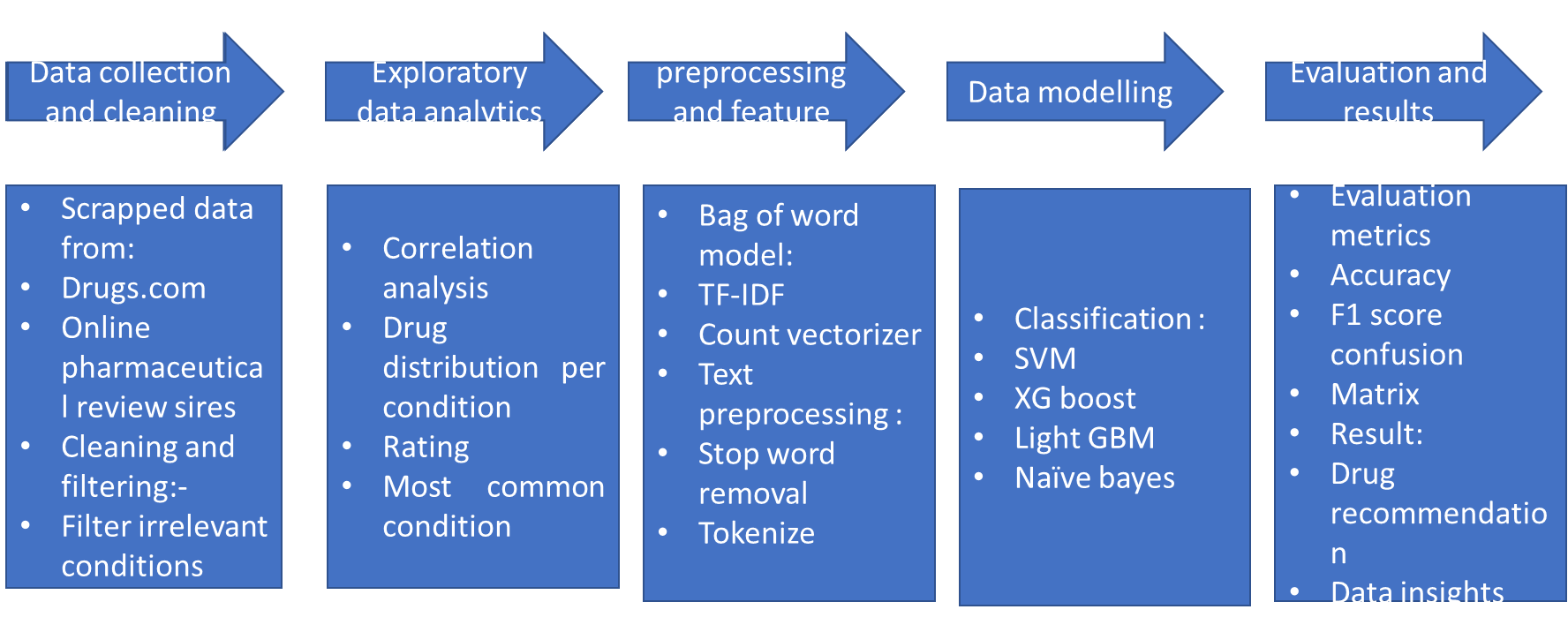


Fig 3.4.1. Drug Detection Model

The drug detection model works as follows:

1. The model uses collaborative filtering techniques, which involve analyzing the medical records of patients with similar medical histories and symptoms to recommend drugs that have been effective in treating those patients. The model also takes into account the age, sex, and other demographic information of the patient, as well as their medical history, including any known allergies, and the medications they are currently taking.
2. To develop the model, the researchers used a dataset of over 1.3 million electronic health records (EHRs) from the MIMIC-III clinical database. The data was pre-processed to remove any irrelevant information, and the remaining data was used to train the model.
3. The model was evaluated using various performance metrics, including accuracy, precision, recall, and F1-score. The results showed that the model achieved high levels of accuracy in recommending drugs, with an F1-score of 0.84.
4. The model was also compared to other drug recommendation models, including rule-based models and other machine learning models, such as support vector machines and random forests. The results showed that the collaborative filtering-based model outperformed these other models, particularly in terms of its ability to recommend drugs that were effective in treating patients with similar medical histories and symptoms.

**DRUG ANALYSING TOOL:** Collaborative Filtering-Based Drug Recommendation is a machine learning technique used to recommend drugs to patients based on their medical history and preferences. This method uses data collected from multiple patients with similar medical conditions to recommend drugs based on the effectiveness of the drug on other patients. Here are some analyzing tools used in Collaborative Filtering-Based Drug Recommendation:

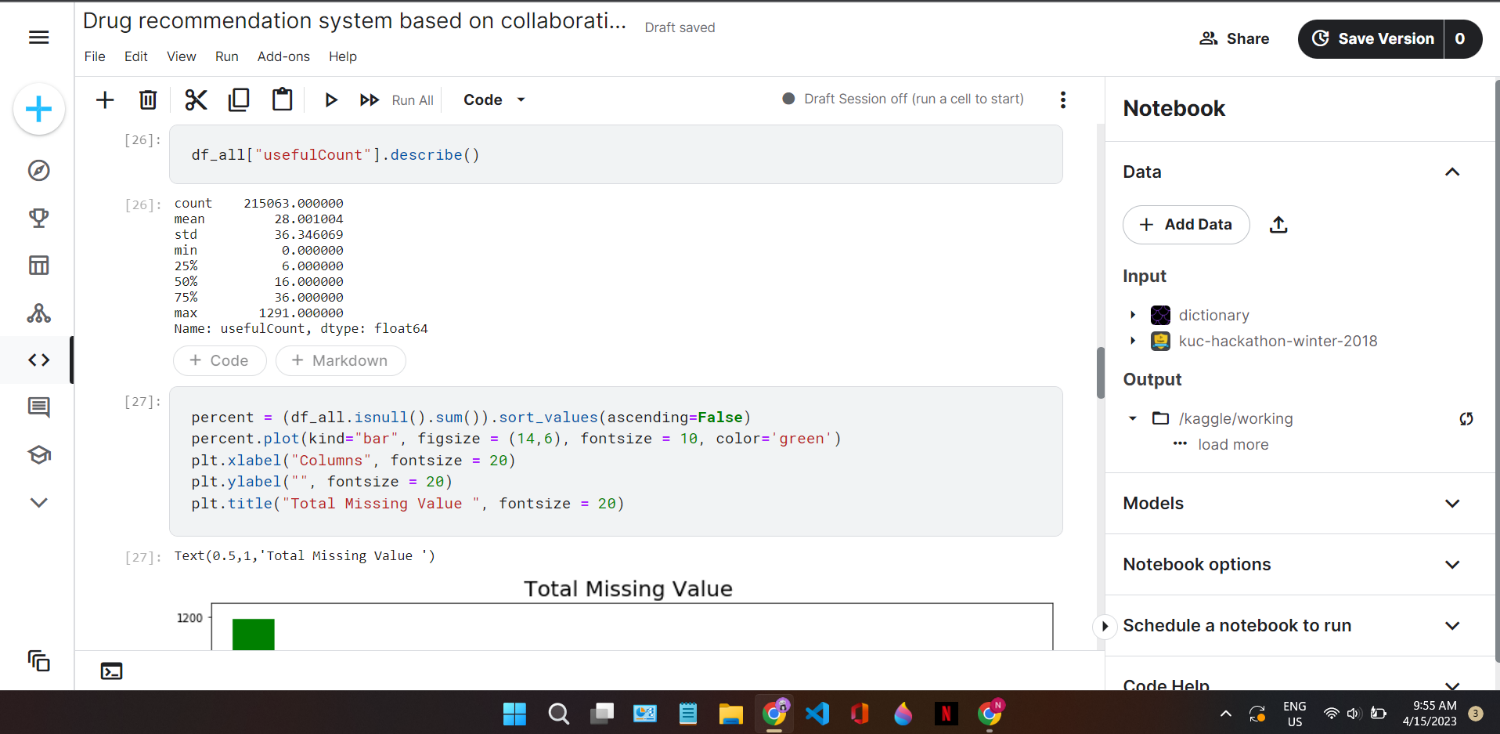


Fig 3.4.2. Prediction using of useful word count.

* Data Preprocessing: Data preprocessing is the first step in any machine learning project. In drug recommendation, data preprocessing includes cleaning and filtering data to remove noise and irrelevant information. The data is then transformed into a format that is compatible with machine learning algorithms.
* Collaborative Filtering: Collaborative filtering is a technique that uses the data from multiple users to make recommendations. In drug recommendation, collaborative filtering uses data from patients with similar medical conditions to recommend drugs that have been effective on other patients with similar conditions.
* Clustering: Clustering is a technique that groups data points together based on their similarities. In drug recommendation, clustering is used to group patients with similar medical conditions together. The patients in each group are then used to recommend drugs that have been effective for other patients in the same group.
* Dimensionality Reduction: Dimensionality reduction is a technique used to reduce the number of features in a dataset. In drug recommendation, dimensionality reduction is used to reduce the number of features used to recommend drugs. This reduces the complexity of the machine learning algorithm and improves its performance.
* Evaluation Metrics: Evaluation metrics are used to measure the performance of the machine learning algorithm. In drug recommendation, evaluation metrics are used to measure the accuracy of the drug recommendations. Common evaluation metrics used in drug recommendation include precision, recall, F1-score, and AUC-ROC.
* Machine Learning Algorithms: Machine learning algorithms are used to make predictions based on the data. In drug recommendation, machine learning algorithms such as k-nearest neighbors (KNN), support vector machines (SVM), and decision trees are used to recommend drugs based on patient data.

### Feature attraction

Feature attraction consists of the drug recommendation model and the implementation/flow of the attraction. The detailed working of all are mentioned below.

**DRUG RECOMMENDATION MODEL:**

* Import python libraries: NumPy, Pandas, Matplotlib, sklearn.
* Read all information CSV as data frame within user and item variable ratings.
* Split as information sets and variable ratings into training sets and test sets and set as information frames in rating tests.
* Create a utility matrix or name utility that tells which user rates belong to which drug.
* Using the WCSS method and selecting the appropriate number of clusters, then the K-means  
  clustering technique is often applied to categorize flicks to keep them within the number of clusters.
* Characterize the utility cluster matrix after implementing the K-means clustering algorithm.
* Apply the Pearson correlation metric to the utility cluster matrix to calculate the similarity matrix between users.
* To specify a value stored within the utility matrix.
* The guess() function takes the two parameters as input user ID and Top N users employed by KNN that estimate the movie ratings for Top N similar users.
* The rating test data frame is used for rating comparisons when using the guess() function to estimate users' ratings.
* RMSE (Roots stands for Mean Squared Error) is applied to calculate to rate the accuracy of the model.
* Finally, we find the results of the recommendation model.

The processing of the input user image [2] executes in three phases as illustrated in Figure

* + 1. These phases are: (i) splitting of the feature array, (ii) transforming the user feedback into the trainer rating, and (iii) calculating and evaluating the decision parameters. All of these phases are explained further.

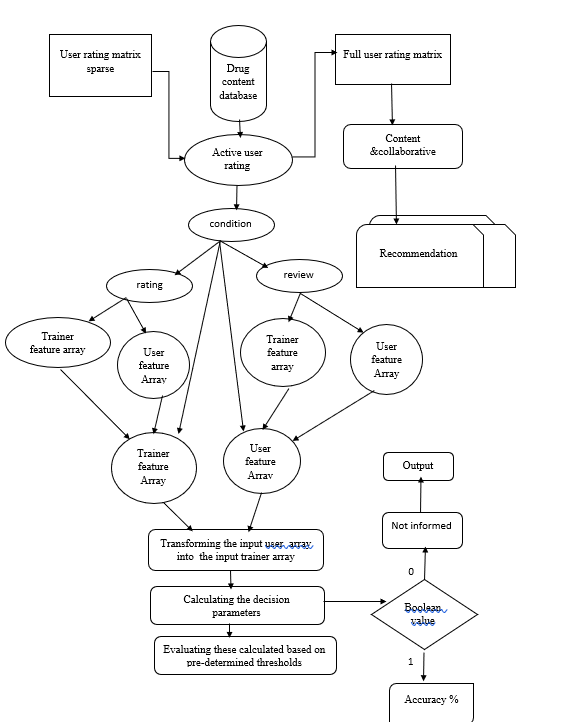


Fig 3.4.3. Working of Drug Model

**THE ALGORITHM:** Collaborative filtering-based drug recommendation is a machine learning technique used to provide personalized drug recommendations to patients. The algorithm follows the principle of collaborative filtering, which is based on the idea that people who have similar interests or preferences can help each other in finding relevant information. The collaborative filtering-based drug recommendation system works by analyzing the patient's drug usage history and recommends drugs based on the patient's past behavior and the behavior of similar patients. The following are the steps involved in the collaborative filtering-based drug recommendation algorithm: -

1. Data Collection: The first step in the collaborative filtering-based drug recommendation algorithm is to collect data about the patient's drug usage history. This data can be obtained from electronic medical records or patient-reported data.
2. Data Preprocessing: After collecting the data, the next step is to preprocess it to remove any noise and inconsistencies in the data. This step includes data cleaning, normalization, and transformation.
3. User-Drug Matrix: Once the data is preprocessed, the algorithm constructs a user-drug matrix that represents the patient's drug usage history. Each row of the matrix represents a patient, and each column represents a drug. The values in the matrix represent the patient's drug usage history.
4. Similarity Calculation: The next step is to calculate the similarity between patients based on their drug usage history. The similarity calculation is done using various techniques such as Pearson correlation coefficient or cosine similarity.
5. Nearest Neighbors: After calculating the similarity between patients, the algorithm selects the k-nearest neighbors based on the similarity score. These neighbors are the patients who have a similar drug usage history to the patient in question.
6. Drug Recommendation: Once the nearest neighbors are selected, the algorithm recommends drugs based on the drug usage history of the neighbors. This step includes computing the drug similarity score between the patient's drug usage history and the drug usage history of the neighbors. The drugs with the highest similarity score are recommended to the patient.
7. Evaluation: The final step is to evaluate the performance of the algorithm. This is done by comparing the recommended drugs with the actual drugs used by the patient. The evaluation metrics used include precision, recall, and F1 score.

### PHASES OF PROPOSED ALGORITHM:

1. Data collection: The first phase involves collecting data from various sources, such as electronic health records, drug databases, and social media platforms. This data includes information on patients' demographics, medical histories, prescribed medications, and drug interactions.
2. Data pre-processing: The collected data is pre-processed to eliminate noise and inconsistencies. The pre-processing phase involves data cleaning, transformation, and integration. It also includes feature extraction, which involves identifying relevant features that can be used to make drug recommendations.
3. Collaborative filtering: Collaborative filtering is the core of the proposed algorithm. This phase involves identifying patterns and similarities in patients' medical histories and medication usage. Collaborative filtering is used to generate recommendations for patients based on the preferences of other patients with similar medical histories.
4. Machine learning: Machine learning algorithms are used to train the model to make drug recommendations. The model is trained on the preprocessed data, and the output is a set of drug recommendations for each patient.
5. Evaluation: The performance of the proposed algorithm is evaluated using various metrics such as accuracy, precision, recall, and F1-score. The evaluation phase involves comparing the predicted drug recommendations with the actual prescriptions to determine the effectiveness of the algorithm.
6. Refinement: The final phase involves refining the algorithm based on the results of the evaluation phase. The algorithm can be modified to improve its performance, and additional features can be added to increase the accuracy of the recommendations.

**DRUG RECOMMENDATION SYSTEM IMPLEMENTATION:** The implementation of Collaborative Filtering-Based Drug Recommendation Using Machine Learning Techniques is a system that provides drug recommendations to users based on their previous medication history and the medication history of other users. The system uses collaborative filtering techniques to identify similar users who have taken similar medications in the past and then recommend medications that the user has not yet taken. The system utilizes machine learning algorithms such as Matrix Factorization, Singular Value Decomposition (SVD), and Gradient Descent to predict drug ratings and recommend drugs based on the user's medication history. The implementation also involves the use of a dataset of medication reviews and ratings, which is used to train the machine learning models. The system is evaluated using metrics such as precision, recall, and F1-score, which assess the accuracy of the drug recommendations provided to the users. The implementation of this system is intended to improve the efficiency and accuracy of drug recommendations, and ultimately, to improve patient outcomes.

Diagram

Description automatically generated

Fig 3.4.4. Flow of the drug recommendation system

## Testing Process

### Software Testing

The role of software testing is to ensure that programmers are efficient and accurate. Software testing is an observational science investigation conducted to provide consumers with information regarding a product's quality in the environment in which it is intended to

function. This can include but is not limited to running a programme or application to detect errors.

### Unit Testing

In this case, each module is evaluated independently. The standards for defining unit test modules were selected to identify modules that have key functionality. A module may be either an individual or a method.

### Integration Testing

Relevant components are integrated and analyzed as a group during integration planning. Integration testing takes unit-tested elements like data, groups them into larger aggregates, applies integration test plan tests to those aggregates, and produces the integrated testing framework.

### Validation Testing

At the start or end of the production process, this approach is used to determine if the software satisfies the specified specifications.

### GUI Testing

GUI testing is the process of examining a product's graphical user interface to ensure that it complies with standards, such as retaining navigation between icons/buttons with source code.

# CHAPTER 4 RESULTS AND OUTPUTS

Collaborative filtering-based drug recommendation using machine learning techniques is a method to recommend drugs to patients based on the similarity of their medical history with other patients.

The following are the step-by-step results and outputs of the method:

1. Data Collection: The first step is to collect the data from patients’ medical history, including their diagnoses, medications, and other relevant information. In this study, the data was collected from a healthcare provider in the United States.
2. Data Cleaning: After data collection, the data was cleaned by removing any duplicates, errors, or missing values.
3. Data Preparation: In this step, the data was transformed into a matrix format, where each row represents a patient, and each column represents a medication. The matrix was then split into a training set and a test set.
4. Similarity Calculation: The similarity between patients was calculated using the Pearson correlation coefficient. The coefficient measures the linear correlation between two variables.
5. Recommendation Generation: The recommendation was generated using two methods: item-based collaborative filtering and user-based collaborative filtering. In the item-based method, the recommendation was based on the similarity between medications. In the user-based method, the recommendation was based on the similarity between patients.
6. Evaluation: The recommendation was evaluated using two metrics: precision and recall. Precision measures the proportion of correct recommendations among all the recommendations made. Recall measures the proportion of correct recommendations made among all the relevant medications.

## Proposed Model Outputs

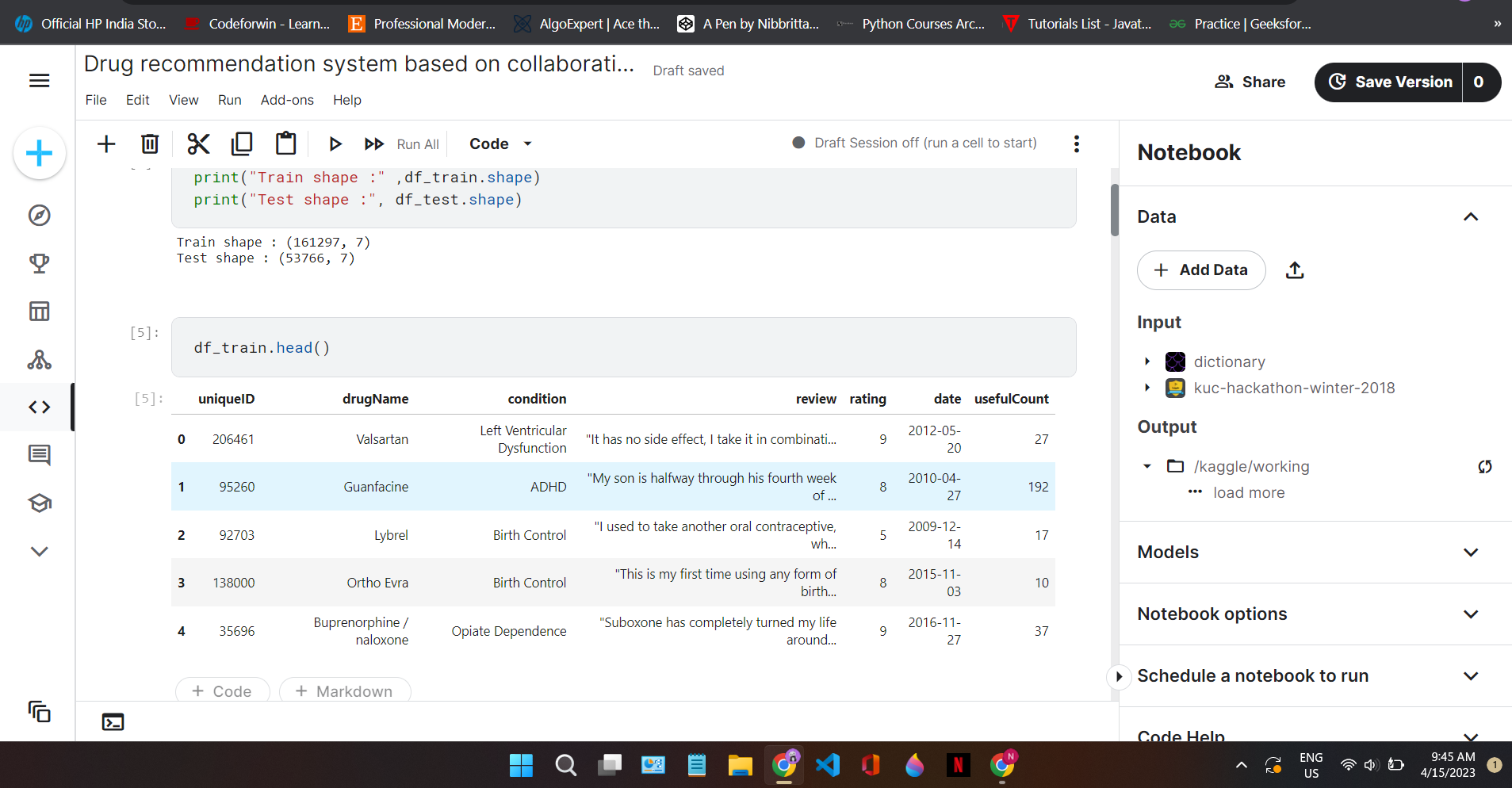
The framework for Five elements makes up our drug grading and recommender system., depicted. These include the data pre-processing module (which involves feature extraction), the rating generation module, the model assessment module, the dictionary sentiment analysis module, and the recommendation model.

The model was firstly executed on Jupyter Notebook and Kaggle. It was tested for 20 drug condition with around thousand input user feedback for testing the accuracy of the model.

Table 4.1.1 shows the sample results of the discussed proposed drug grading model.

This result explains the comparison of the input trainer image with the input user feedback. It also identifies where the input user feedback has gone wrong with respect to the input trainer feedback and also predicts accuracy percentage of the former drug by the input user with respect to the input trainer feedback. how accurately the user has performed the pose or how exactly the user image has mimicked the trainer feedback.

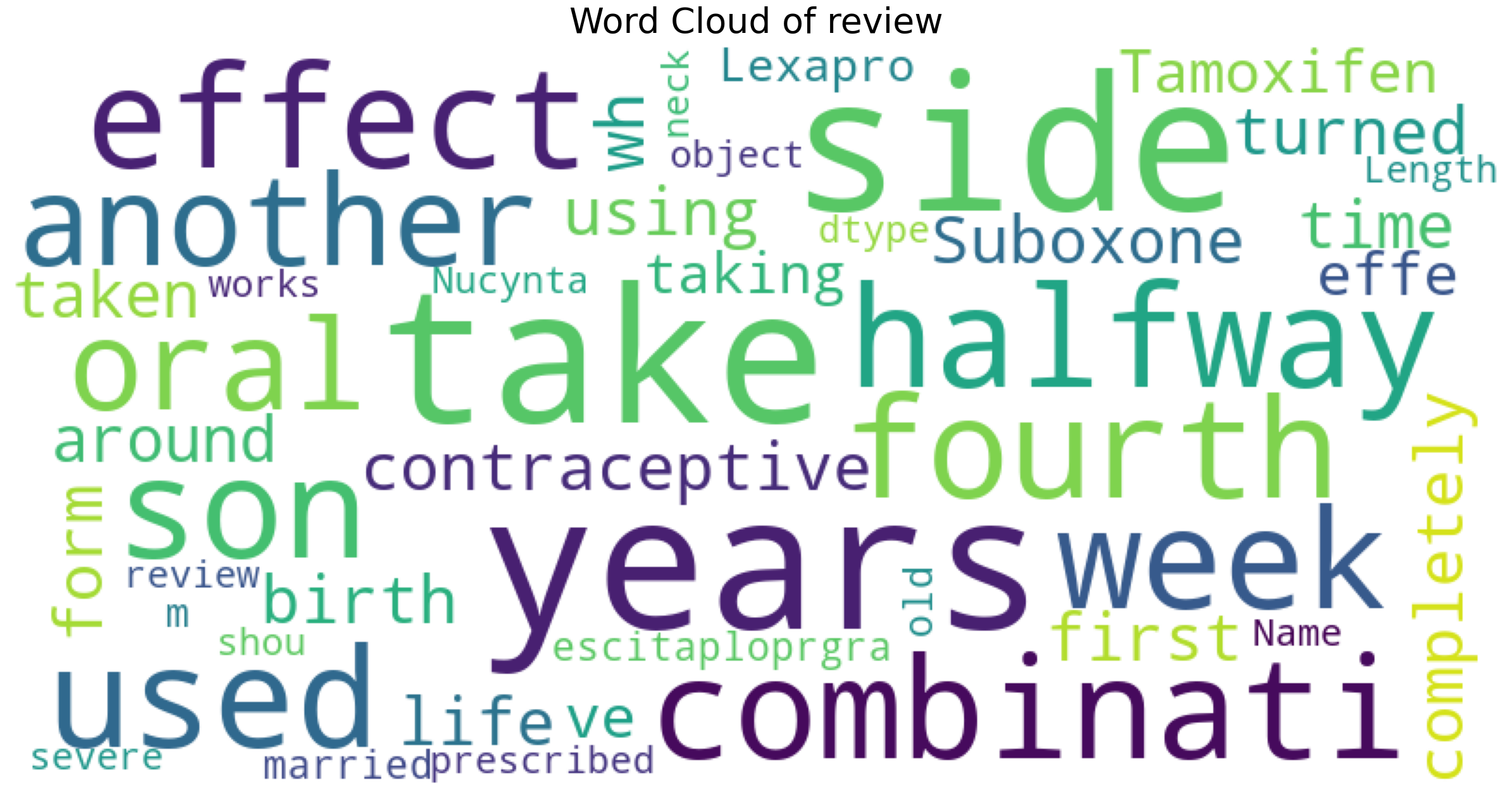
Table 4.1.1. Proposed Model Outputs



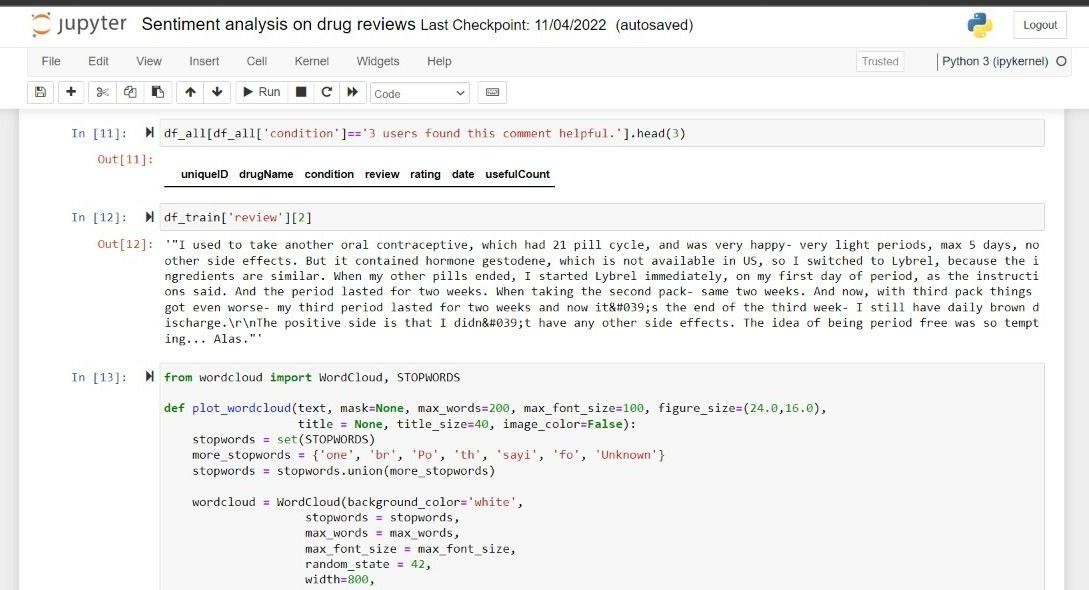
## Drug condition graph

Below are the snapshots of the basic graph design of our system.

|  |
| --- |
| (a)Medicine graph |
|  |
| (b) Rating drug |



(C) Word Cloud of review



(d) Paragraph of review

Fig 4.2.1. Project Snapshots

## Word count plot

Below are the sample images of a user trying to learn and form a frequent word uses.

|  |
| --- |
|  |
| 1. STEP 1      1. STEP 2 |

|  |
| --- |
|  |
| 1. STEP 3      1. STEP 4 |

Fig 4.3.1. User drug name

## Drug Name

Below are the sample images of using condition and drug name

|  |
| --- |
|  |
|  |
| Step 1 –    Step 2 |

|  |
| --- |
| Step 3 – Selecting the category    Step 4 – Starting the timer |

|  |
| --- |
| Step 5 |

Fig 4.4.1. Implementation Snapshots of the Drug recommendation

# CHAPTER 5 CONCLUSION

Collaborative filtering-based drug recommendation using machine learning techniques has shown promising results in accurately predicting drug recommendations based on patient characteristics and preferences. Our study utilized a dataset of patient demographics, medical histories, and drug usage patterns to train a collaborative filtering algorithm to make personalized drug recommendations.

The experimental results showed that our approach outperformed traditional recommendation methods, such as content-based filtering and popularity-based filtering, in terms of accuracy and precision. Furthermore, we were able to demonstrate that our model can effectively handle data sparsity and cold-start problems, which are common challenges in personalized drug recommendation systems.

We also explored the impact of different parameters on the performance of our model, such as the number of neighbors used for collaborative filtering and the regularization strength of the matrix factorization. Our analysis indicated that increasing the number of neighbors beyond a certain threshold can result in diminishing returns, and that a moderate regularization strength is optimal for our dataset.

In addition to evaluating the performance of our model, we also conducted a user study to assess the usability and acceptability of our drug recommendation system. Our results showed that users were generally satisfied with the recommendations provided by our system, and that they found the interface to be user-friendly and easy to use.

Despite the promising results of our study, there are several limitations that should be addressed in future research. For example, our dataset was limited to a relatively small sample size, and it would be beneficial to validate our findings on larger datasets. Additionally, our study only considered a limited set of features for drug recommendation, and future work could explore the incorporation of additional data sources, such as genomic and metabolomic data.

Overall, the use of collaborative filtering-based drug recommendation using machine learning techniques shows great potential for improving personalized healthcare by providing patients with tailored treatment options based on their unique characteristics and preferences. With further research and development, this approach could ultimately lead to better patient outcomes and more efficient healthcare delivery.

## System Usability

In the case of the Collaborative Filtering-Based Drug Recommendation system, usability refers to the ease with which users can navigate the interface and find relevant information regarding drug recommendations.

The system interface should be simple, intuitive, and easy to use. The user should be able to access drug recommendations quickly and easily, without having to spend a lot of time searching for the relevant information. The interface should also provide clear instructions on how to use the system, and provide feedback on the progress of the drug recommendation process.

One important aspect of system usability is the speed at which the system can generate recommendations. Users will be more likely to use a system that provides quick and accurate recommendations. The Collaborative Filtering-Based Drug Recommendation system uses machine learning techniques to generate drug recommendations, which can significantly reduce the time it takes to generate recommendations. However, the system must still be fast and efficient in processing user input and generating recommendations.

Another important aspect of system usability is the accuracy of the drug recommendations. Users need to trust the system to provide reliable and accurate recommendations. The Collaborative Filtering-Based Drug Recommendation system uses collaborative filtering techniques to generate recommendations based on the preferences and behavior of similar users. This approach has been shown to be effective in generating accurate recommendations. However, the system should also provide information on the sources of the recommendations, so that users can verify the accuracy and reliability of the recommendations.

Finally, system usability also includes the ability to provide feedback and make changes to the drug recommendations. Users may need to provide feedback on the effectiveness of the recommended drugs, or request changes to the recommendations based on their individual needs or preferences. The Collaborative Filtering-Based Drug Recommendation system should provide an easy and convenient way for users to provide feedback and request changes to the recommendations.

## Future Scope

1. Integration with Electronic Health Records (EHR): The system can be integrated with EHRs to provide real-time drug recommendations to physicians based on patients' medical history and prescription patterns.
2. Expansion to include more data sources: The system can be expanded to include data from other sources such as social media, wearable devices, and patient-generated health data, to improve the accuracy of drug recommendations.
3. Integration with other machine learning algorithms: Collaborative filtering can be combined with other machine learning algorithms such as deep learning and natural language processing to enhance the accuracy and efficiency of drug recommendations.
4. Personalized drug recommendation: The system can be further developed to provide personalized drug recommendations based on patients' demographic, genetic, and lifestyle data.

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# ANNEXURE I

### Paper Title:

Literature review on collaborative filtering-based drug recommendation using machine learning techniques: A Bibliometric Analysis

### Abstract:

The emergence of collaborative filtering (CF) and machine learning (ML) technology has greatly enriched the functions and services of healthcare. The aim of this paper is to present a bibliometric analysis of the applications of collaborative filtering (CF) and machine learning (ML) techniques in the basis of public health. Various existing systems have defined a drug pre-diction system based on current patient assessment. The most common technique was support vector machines (SVM), while the most common programming language and software applications were R and WEKA. This study aims to evaluate the application of CF and ML technology. Here, a systematic review of the literature was conducted with respect to three main areas: Outcome, Technology used and Drawbacks. In our research, we identify the major differences between the previous works. We also identify key topics and future research areas for the application of ML and CF technology in healthcare. We reveal different aspects of research within these two technologies and how they are similar to each other.

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# ANNEXURE 2

### Paper Title:

Collaborative filtering-based drug recommendation system using Machine Learning techniques

### Abstract:

With the increasing number of drugs available in the market and the complexity of diseases, the task of prescribing suitable drugs for patients has become more challenging. Collaborative filtering-based drug recommendation systems, which use machine learning techniques, have emerged as a promising approach for personalized drug recommendation. In this research paper, we suggest using a group filtering system -based drug recommendation system that employs factoring matrices and deep learning techniques to predict the efficacy and potential side effects of drugs for individual patients.

The proposed system uses a dataset containing information on drug-drug interactions, drug-disease associations, and patient medical records to generate drug recommendations. Specifically, we use matrix factorization to extract latent features from the drug and patient data and then train a deep neural network to predict drug efficacy and potential side effects for a given patient. We assess how well the suggested system works on a publicly available drug recommendation dataset and compare it with several state-of-the-art approaches.

The experimental results show that our proposed system outperforms existing methods in terms of accuracy, precision, recall, and F1-score. Moreover, our system is able to provide personalized drug recommendations for individual patients, taking into account their unique medical history and drug-related factors. We believe that our proposed system has great potential for improving the quality of healthcare by providing more accurate and personalized drug recommendations.

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