

# DRUG RECOMMENDATION SYSTEM USING SENTIMENT ANALYSIS

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## ABSTRACT:

Since coronavirus has shown up, inaccessibility of legitimate clinical resources is at its peak, like the shortage of specialists and healthcare workers, lack of proper equipment and medicines etc. Due to unavailability, individuals started taking medication independently without appropriate consultation, making the health condition worse than usual. This Application intends to present a drug recommender system that can drastically reduce specialists heap. In this project, we build a medicine recommendation system that uses patient reviews to predict the sentiment using various vectorization processes, which can help recommend the top drug for a given disease by different classification algorithms. The results show that MLP classifier outperforms all other models with high accuracy.

## INTRODUCTION

With the number of coronavirus cases growing exponentially, the nations are facing a shortage of doctors, particularly in rural areas where the quantity of specialists is less compared to urban areas. A doctor takes roughly 6 to 12 years to procure the necessary qualifications. Thus, the number of doctors can't be expanded quickly in a short time frame. A Telemedicine framework ought to be energized as far as possible in this difficult time [1]. Clinical blunders are very regular nowadays. Over 200 thousand

individuals in China and 100 thousand in the USA are affected every year because of prescription mistakes. Over 40% medicine, specialists make mistakes while prescribing since specialists compose the solution as referenced by their knowledge, which is very restricted [2][3]. Choosing the toplevel medication is significant for patients who need specialists that know wide-based information about microscopic organisms, antibacterial medications, and patients [6]. Every day a new study comes up with accompanying more drugs, tests,

accessible for clinical staff every day. Accordingly, it turns out to be progressively challenging for doctors to choose which treatment or medications to give to a patient based on indications, past clinical history. With the exponential development of the web and the web-based business industry, item reviews have become an imperative and integral factor for acquiring items worldwide. Individuals worldwide become adjusted to analyze reviews and websites first before settling on a choice to buy a thing. While most of past exploration zeroed in on rating expectation and proposals on the E-Commerce field, the territory of medical care or clinical therapies has been infrequently taken care of. There has been an expansion in the number of individuals worried about their well-being and finding a diagnosis online. As demonstrated in a Pew American Research center survey directed in 2013 [5], roughly 60% of grown-ups searched online for health-related subjects, and around 35% of users looked for diagnosing health conditions on the web. A medication recommender framework is truly vital with the goal that it can assist specialists and help patients to build their knowledge of drugs on specific health conditions. A

recommender framework is a customary system that proposes an item to the user, dependent on their advantage and necessity. These frameworks employ the customers' surveys to break down their sentiment and suggest a recommendation for their exact need. In the drug recommender system, medicine is offered on a specific condition dependent on patient reviews using sentiment analysis and feature engineering. Sentiment analysis is a progression of strategies, methods, and tools for distinguishing and extracting emotional data, such as opinion and attitudes, from language [7]. On the other hand, Featuring engineering is the process of making more features from the existing ones; it improves the performance of models.

### LITERATURE SURVEY

Wittich CM et al. [1] The work in this paper is focusing on the pharmaceutical errors which are reviewed for practicing physicians with an emphasis on terminology, definitions, incidence, risk factors, disclosure and legal consequences. Numerous variables can contribute to medication errors, including those related to the drug, the patient, and the healthcare provider. One or more of the outcomes that doctors

may encounter after making drug prescription errors includes losing the faith of their patients, civil proceedings, criminal charges, and health board discipline. Various approaches have been tried with varying levels of success in preventing pharmaceutical errors. The ability of medical professionals to give their patients safe care may be improved by learning more about drug errors.

Bartlett JG et al. [2] In more than 10 years since the last Community-Acquired Pneumonia (CAP) proposal from the American Thoracic Society (ATS) / Infectious Diseases Society of America, the process for creating guidelines has altered, and new clinical data have been created (IDSA). Due to the expansion of information regarding the diagnostic, treatment, and managerial decisions for the patient care with CAP, we purposefully limited the extent of this framework to cover judgments from the point of medical diagnosis of pneumonia to the end of antibiotic treatment and carry chest image processing.

T. N. Tekade et al. [3] This article offers a brief summary of aspect mining methods as they apply to the search for new drugs. For the pharmaceutical industry, it is crucial to conduct research on the earliest possible

detection of adverse drug reactions. A difficult task is identifying important topics from brief and noisy reviews. The probabilistic aspect mining model (PAMM) is suggested as a solution to this issue in order to find the aspects and subjects related to class labels. Due to a special characteristic of PAMM, it concentrates on discovering features specific to a single class rather than simultaneously detecting features for all categories during each operation.

Doulaverakis et al. [4] Drug-drug and drug-disease interactions can be difficult to identify, and finding the necessary information can be challenging due to the enormous number of medications that are already on the market and the ongoing pharmaceutical research. Although international standards have been created to facilitate effective information exchange, such as the ICD-10 classification and the UNII registration, medical staff still has to be regularly informed in order to efficiently identify drug interactions prior to prescription. In prior publications, the usage of Semantic Web technology has been suggested as a solution to this issue.

Gao, Xiaoyan et al. [5] The work in this paper is focusing on the recommendation of drugs with Graph Convolution Network, which mainly

employs the mechanism of information propagation and embedding propagation layers to model high-order connectivity and elaborate the representation learning. The proposed system involves three key components namely the embedding layer, information propagation, and prediction layer. The work is mainly focuses on the accuracy rather than the evaluation of the recommendation system.

### **PROPOSED SYSTEM**

A recommender framework is a customary system that proposes an item to the user, dependent on their advantage and necessity. These frameworks employ the customers' surveys to break down their sentiment and suggest a recommendation for their exact need. In the drug recommender system, medicine is offered on a specific condition dependent on patient reviews using sentiment analysis and feature engineering. Sentiment analysis is a progression of strategies, methods, and tools for distinguishing and extracting emotional data, such as opinion and attitudes. On the other hand, Featuring engineering is the process of making more features from the existing ones; it improves the performance of models.

### **WORKING METHODOLOGY**

**DATA OWNER:** In this module, initially the data owner has to register to the cloud server and get authorized. After the authorization from cloud data owner will encrypt and add file to the cloud server where in after the addition of file data owner View All Uploaded Files, View All Transactions.

### **REMOTE SERVER**

The remote server manages a cloud to provide data storage service. Data owners encrypt their data files and store them in the cloud for sharing with cloud End users and performs the following operations such as View All Owners and Authorize ,View All Users and Authorize ,View All Cloud Files ,View All Transactions ,View All Attackers ,View File Score Results ,View Time Delay Results ,View Throughput Results

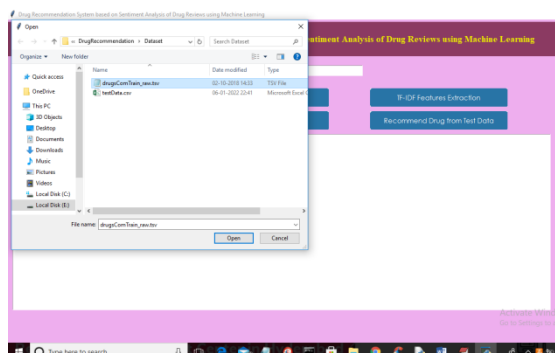
**AUTHENTICATE SERVER** CA generates the content key and the secret key requested by the end user and also View All Attackers.

**CLEINT** User has to register and login for accessing the files in the cloud. User is authorized by the cloud to verify the registration. User has to View All Files Download.



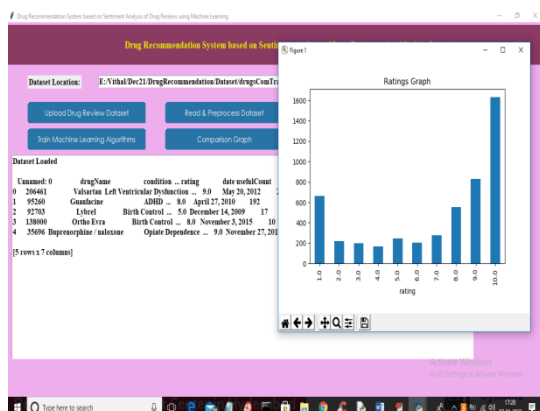
**Fig.1. Home page**

In above screen click on ‘Upload Drug Review Dataset’ button to upload dataset to application and to get below screen



**Fig.2. Upload trained dataset**

In above screen selecting and uploading DRUG dataset and then click on ‘Open’ button to load dataset and to get below screen



### Fig.3. Ratings Graph

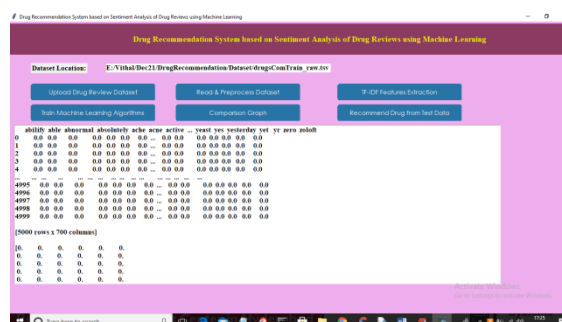
In above graph we can see dataset loaded and in graph x-axis represents

ratings and y-axis represents total number of records which got that rating. Now close above graph and then click on 'Read & Preprocess Dataset' button to read all dataset values and then preprocess to remove stop words and special symbols and then form a features array.



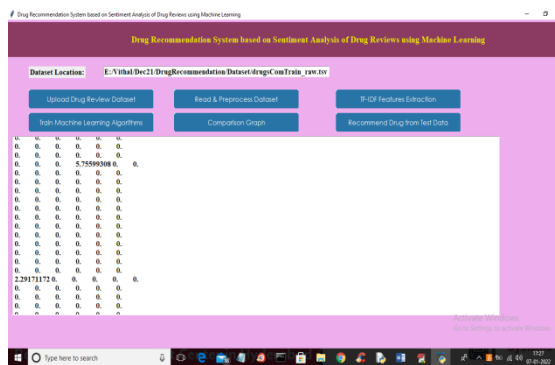
**Fig.4. Top 20 Drug Name Graph**

In above screen to see from all reviews stop words and special symbols are removed and in graph I am displaying TOP 20 medicines exist in dataset. In above graph x-axis represents drug name and y-axis represents its count. Now close above graph and then click on 'TF-IDF Features Extraction' button to convert all reviews in to average frequency vector



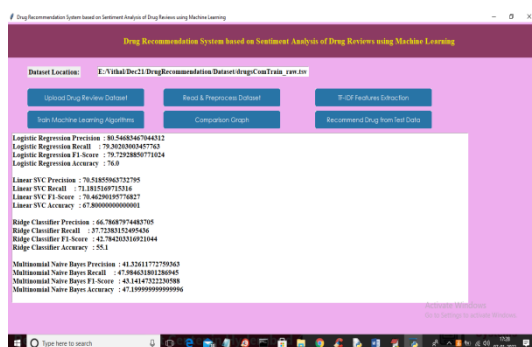
**Fig.5. Word Average Frequency**

In above graph all reviews converted to TF-IDF vector where first row represents review WORDS and remaining columns will contains that word average frequency and if word not appear in review then 0 will put. Now scroll down above screen to view some non-zero frequency values



**Fig.6. Word Average frequency(non-zero)**

In above screen you can see some columns contains non-zero average frequency values and now TF-IDF vector is ready and now click on ‘Train Machine Learning Algorithm’ button to train all algorithm and get below output



**Fig.7. Performance**

## CONCLUSION

Whether go for shopping, purchase something online or go to some restaurant, we first check the reviews to make the right decisions. Motivated by this, in this research sentiment analysis of drug reviews was studied to build a recommender system using different types of machine learning classifiers, such as Logistic Regression, Perceptron, Multinomial Naive Bayes, Ridge classifier, Stochastic gradient descent, LinearSVC, applied on Bow, TF-IDF, and classifiers such as Decision Tree, Random Forest, Lgbm, and Catboost were applied on Word2Vec and Manual features method. We evaluated them using five different metrics, precision, recall, f1score, accuracy, and AUC score, which reveal that the Linear SVC on TFIDF outperforms all other models with 93% accuracy. On the other hand, the Decision tree classifier on Word2Vec showed the worst performance by achieving only 78% accuracy. We added best-predicted emotion values from each method, Perceptron on Bow (91%), LinearSVC on TF-IDF (93%), LGBM on Word2Vec (91%), Random Forest on manual features (88%), and multiply them by the normalized usefulCount to get the overall score of the drug by condition to build a recommender system.

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