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Drug Recommendation System based on Sentiment Analysis of Drug Reviews using Machine Learning

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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. The entire medical fraternity is in distress, which results in numerous individual's demise. Due to unavailability, individuals started taking medication independently without appropriate consultation, making the health condition worse than usual. As of late, machine learning has been valuable in numerous applications, and there is an increase in innovative work for automation. This project intends to present a drug recommender system that can drastically reduce specialists heap. In this project, build a medicine recommendation system that uses patient reviews to predict the sentiment using various vectorization processes like Bow, TF-IDF,Word2Vec, and Manual Feature Analysis, which can help recommend the top drug for a given disease by different classification algorithms.

Keywords: - Drug Recommendation, Sentiment Analysis, Drug Reviews, Machine Learning.

I. INTRODUCTION

Due to unavailability, individuals started taking medication independently without appropriate consultation, making the health condition worse than usual. This project intends to present a drug recommender system that can drastically reduce specialists heap. 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.

II. RELATEDWORKS

The study [9] presents GalenOWL, a semantic-empowered online framework, to help specialists discover details on the medications. The paper depicts a framework that suggests drugs for a patient based on the patient's infection, sensitivities, and drug interactions. For empowering GalenOWL, clinical data and terminology first converted to ontological terms utilizing worldwide standards, such as ICD-10 and UNII, and then correctly combined with the clinical information. Leilei Sun [10] examined large scale treatment records to locate the best treatment prescription for patients. The idea was to use an efficient semantic clustering algorithm estimating the similarities between treatment records. Likewise, the author created a framework to assess the adequacy of the suggested treatment. This structure can prescribe the best treatment regimens to new patients as per their demographic locations and medical complications. An Electronic Medical Record (EMR) of patients gathered from numerous clinics for testing. The result shows that this framework improves the cure rate. In this research [11], multilingual sentiment analysis was performed using Naive Bayes and Recurrent Neural Network (RNN). Google translator API was used to convert multilingual tweets into the English language. The results exhibit that RNN with 95.34% outperformed Naive Bayes, 77.21%. The study [12] is based on the fact that the recommended drug should depend upon the patient's capacity. For example, if the patient's immunity is low, at that point, reliable medicines ought to be recommended. Proposed a risk level classification method to identify the patient's immunity. For example, in excess of 60 risk factors, hypertension, liquor addiction, and so forth have been adopted, which decide the patient's capacity to shield himself from infection. A web-based prototype system was also created, which uses a decision support system that helps doctors select first-line drugs.

Xiaohong Jiang et al. [13] examined three distinct algorithms, decision tree algorithm, support vector machine (SVM), and backpropagation neural network on treatment data. SVM was picked for the medication proposal module as it performed truly well in each of the three unique boundaries - model exactness, model proficiency, model versatility. Additionally, proposed the mistake check system to ensure analysis, precision and administration quality. Mohammad Mehedi Hassan et al. [14] developed a cloudassisted drug proposal (CADRE). As per patients' side effects, CADRE can suggest drugs with top-N related prescriptions. This proposed framework was initially founded on collaborative filtering techniques in which the medications are initially bunched into clusters as indicated by the functional description data. However, after considering its weaknesses like computationally costly, cold start, and information sparsity, the model is shifted to a cloud-helped approach using tensor decomposition for advancing the quality of experience of medication suggestion. Considering the significance of hashtags in sentiment analysis, Jiugang Li et al. [15] constructed a hashtag recommender framework that utilizes the skip-gram model and applied convolutional neural networks (CNN) to learn semantic sentence vectors. These vectors use the features to classify hashtags using LSTM RNN. Results depict that this model beats the conventional models like SVM, Standard RNN. This exploration depends on the fact that it was undergoing regular AI methods like SVM and collaborative filtering techniques; the semantic features get lost, which has a vital influence in getting a decent expectation.

III. PROPOSED SYSTEM ARCHITECTURE

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 . On the other hand, Featuring engineering is the process of making more features from the existing ones; it improves the performance of models. The system is more effective since it presents the proposed algorithm used in natural language processing responsible for counting the number of times of all the tokens in review or document. The system has exact sentiment analysis prediction techniques for Data Cleaning and Visualization.

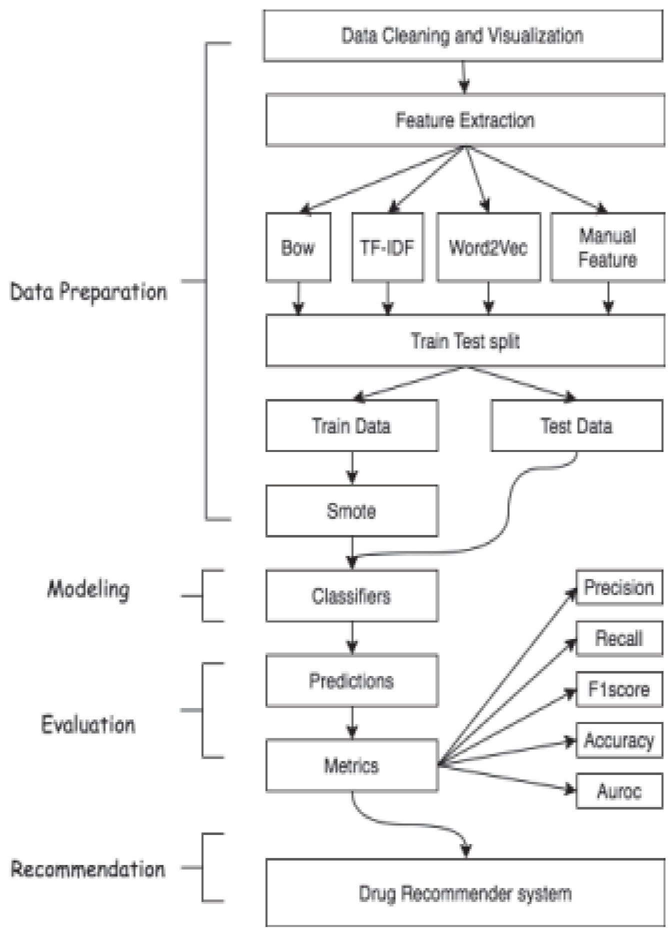

Fig.1 Proposed system process flow

IV. RESULTS AND DISCUSSION

In this work, each review was classified as positive or negative, depending on the user's star rating. Ratings above five are classified as positive, while negative ratings are from one to five-star ratings. Initially, the number of positive ratings and negative ratings in training data were 111583 and 47522, respectively. After applying smote, we increased the minority class to have 70 percent of the majority class examples to curb the imbalances. The updated training data contains 111583 positive classes and 78108 negative classes. Four different text representation methods, namely Bow, TF-IDF, Word2Vec, Manual feature and ten different ML algorithms were applied for binary classification.

After evaluating all the models, the prediction results of Perceptron (Bow), LinearSVC (TF-IDF), LGBM (Word2Vec), and RandomForest (Manual Features) was added to give combined model predictions. The main intention is to make sure that the recommended top drugs should be classified correctly by all four models. If one model predicts it wrong, then the drug's overall score will go down. These combined predictions were then multiplied with normalized useful count to get an overall score of each drug. This was done to check that enough people reviewed that drug. The overall score is divided by the total number of drugs per condition to get a mean score, which is the final score.

The results procured from each of the four methods are good, yet that doesn't show that the recommender framework is ready for real-life applications. It still need improvements. Predicted results show that the difference between the positive and negative class metrics indicates that the training data should be appropriately balanced using algorithms like Smote, Adasyn [24], SmoteTomek [25], etc. Proper hyperparameter optimization is also required for classification algorithms to improve the accuracy of the model. In the recommendation framework, we simply just added the best-predicted result of each method. For better results and understanding, require a proper ensembling of different predicted results. This paper intends to show only the methodology that one can use to extract sentiment from the data and perform classification to build a recommender system. Fig. 2 shows the top four drugs recommended by our model on top five conditions namely, Acne, Birth Control, High Blood Pressure, Pain and Depression.

After assessing the metrics, all four best-predicted results were picked and joined together to produce the combined prediction. The merged results were then multiplied with normalized useful count to generate an overall score of drug of a particular condition. The higher the score, the better is the drug. The motivation behind the standardization of the useful count was looking at the distribution of useful count in Fig. 3; one may analyze that the contrast among the least and most extreme is around 1300, considerable. Moreover, the deviation is enormous, which is 36. The purpose behind is that the more medications individuals search for, the more individuals read the survey regardless of their review is positive or negative, which makes the useful count high. So while building the recommender system, we normalized useful count by conditions.

Distinct machine-learning classification algorithms were used to build a classifier to predict the sentiment. Logistic Regression, Multinomial Naive Bayes, Stochastic gradient descent, Linear support vector classifier, Perceptron, and Ridge classifier experimented with the Bow, TF-IDF model since they are very sparse matrix and applying tree-based classifiers would be very time-consuming. Applied Decision tree, RandomForest, LGBM, and CatBoost classifier on Word2Vec and manual features model. A significant problem with this dataset is around 210K reviews, which takes substantial computational power. We selected those machine learning classification algorithms only that reduces the training time and give faster predictions.

condition	drugName	Score
Acne	Retin-A	0.069334
Acne	Atralin	0.088545
Acne	Magnesium hydroxide	0.088545
Acne	Retin A Micro	0.097399
Birth Control	Mono-Linyah	0.005448
Birth Control	Gildess Fe 1.5 / 30	0.005987
Birth Control	Ortho Micronor	0.006149
Birth Control	Lybrel	0.027766
High Blood Pressure	Adalat CC	0.303191
High Blood Pressure	Zestril	0.305851
High Blood Pressure	Toprol-XL	0.362589
High Blood Pressure	Labetalol	0.367021
Pain	Neurontin	0.158466
Pain	Nortriptyline	0.171771
Pain	Pamelor	0.231829
Pain	Elavil	0.304513
Depression	Remeron	0.124601
Depression	Sinequan	0.146486
Depression	Provigil	0.240185
Depression	Methylin ER	0.328604

Fig.2 Recommendation of top four drugs on top five conditions

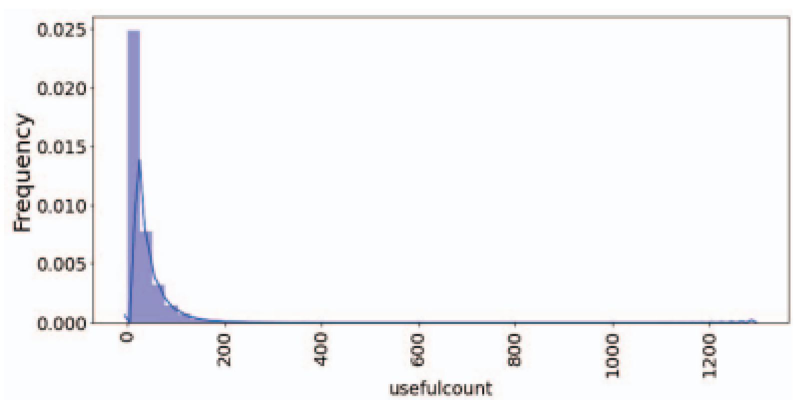

Fig.3 Distribution of useful count

V. FUTURE SCOPE AND CONCLUSION

Reviews are becoming an integral part of our daily lives; 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 TF-IDF 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. Future work involves comparison of different oversampling techniques, using different values of n-grams, and optimization of algorithms to improve the performance of the recommender system

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