International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 10 Issue 7 ǁ July 2022 ǁ PP. 660-665

Recommendation of Drug Based On Its Reviews Using Machine Learning

[1]Roopa D E, [2]Munzeera Sajid C M, [3]K B Gouthami, [4]Pavana M S,[5]Prince Kumar Singh
[1]Assistant Professor, [2]Student, [3]Student, [4]Student, [5]Student
[1]Information Science and Engineering,
[1]Bapuji Institute of Engineering and Technology, Davangere, India

Abstract: *With the development of e-commerce, a growing number of people prefer to purchase medicine online for the sake of convenience. Therefore, more and more people are hearing about the health and medical diagnosis problems. Numerous medication errors are caused by doctors because experts write the prescription according to their experiences which are quite limited. Technologies as data mining and recommender technologies provide possibilities to explore potential knowledge from diagnosis history records and help doctors to prescribe medication correctly to decrease medication error effectively. This work intends to present a drug recommender system that can drastically reduce specialists heap. We build a system which recommends a drug based on the reviewsthat predicts whether a drug can be used or not by using ML classification algorithms.*

Index Terms - *drug, recommendation, sentiment analysis*

Date of Submission: 08-07-2022 Date of acceptance: 22-07-2022

I. INTRODUCTION

Health information is one of the most widely concerned topics on the Web. A survey in 2017 by the Pew Internet and American Life Project found that 59% of adults have looked online for health topics, and with 35% of respondents focusing on diagnosing a medical condition online. Behind the data, we find that more and more people are caring about the health and medical diagnosis problem. However, there are still many people losing their lives due to medication errors. According to the administration's report, more than 200 thousand people in China, even 100 thousand in USA, die each year due to medication errors.

More than 42% medication errors are caused by doctors because experts write the prescription according to their experiences which are quite limited.

There are some facts that may lead to these issues:

(i) Many hospitals lack either doctors or medical experts for critical illness,

(ii) Expert diagnosis is mainly depended on the expert's experience, especially for those inexperienced novices, which are hard to avoid mistakes.

Meanwhile, most diagnosis case data in hospitals is still kept untouched and has not been used for mining, so that the value behind the data cannot be explored. Hospital Information System (HIS) generates massive data, how to discover potential and useful knowledge from the diagnosis case data is a big challenge. Data mining and recommender technologies represent a promising direction to solve these challenging problems.

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 this project, it is recommended whether medicine can be used or not based 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.

II. LITERATURE SURVEY

In 2014, **Zhang, Yin & Zhang, Dafang & Hassan, Mohammad & Alamri, Atif & Peng, Limei** propose a novel cloud-assisted drug recommendation (CADRE), which can recommend users with top-N related medicines according to symptoms. In CADRE, they first cluster the drugs into several groups according to the functional description information, and design a basic personalized drug recommendation based on user collaborative filtering. Then, considering the shortcomings of collaborative filtering algorithm, such as

computing expensive, cold start, and data sparsity, we propose a cloud-assisted approach for enriching end-user Quality of Experience (QoE) of drug recommendation, by modeling and representing the relationship of the user, symptom and medicine via tensor decomposition. Finally, the proposed approach is evaluated with experimental study based on a real dataset crawled from Internet. [1]

In 2015, **Danushka Bollegala, Takanori Maehara and Kenichi Kawarabayashi** propose an unsupervised method for learning domain-specific word representations that accurately capture the domain-specific aspects of word semantics. First, they select a subset of frequent words that occur in both domains as \emph{pivots}. Next, they optimize an objective function that enforces two constraints: (a) for both source and target domain documents, pivots that appear in a document must accurately predict the co-occurring non-pivots, and (b) word representations learnt for pivots must be similar in the two domains. Moreover, they propose a method to perform domain adaptation using the learnt word representations. Their proposed method significantly outperforms competitive baselines including the state-of-the-art domain-insensitive word representations, and reports best sentiment classification accuracies for all domain-pairs in a benchmark dataset. [2]

In 2016, **Y. Bao and X. Jiang** design and implement a universal medicine recommender system framework that applies data mining technologies to the recommendation system. The medicine recommender system consists of database system module, data preparation module, recommendation model module, model evaluation, and data visualization module. They investigate the medicine recommendation algorithms of the SVM (Support Vector Machine), BP neural network algorithm and ID3 decision tree algorithm based on the diagnosis data. Experiments are done to tune the parameters for each algorithm to get better performance. Finally, in the given open dataset, SVM recommendation model is selected for the medicine recommendation module to obtain a good trade-off among model accuracy, model efficiency, and model scalability. They also propose a mistake-check mechanism to ensure the diagnosis accuracy and service quality. Experimental results show their system can give medication recommendation with an excellent efficiency, accuracy and scalability. [3]

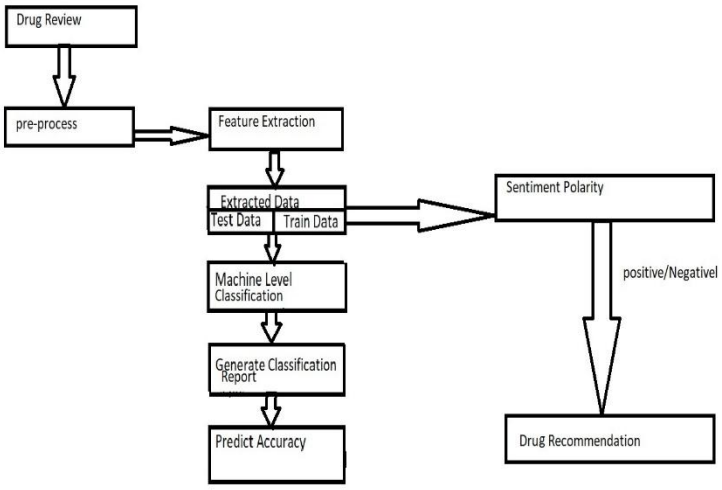
In 2016, **J. Li, H. Xu, X. He, J. Deng and X. Sun** propose a novel recurrent neural network model to learn vector-based tweet representations to recommend hashtags. More precisely, they use a skip-gram model to generate distributed word representations and then apply a convolutional neural network to learn semantic sentence vectors. Afterwards, they make use of the sentence vectors to train a long short-term memory recurrent neural network (LSTM-RNN). They directly use the produced tweet vectors as features to classify hashtags without any feature engineering. Experiments on real world data from Twitter to recommend hashtags show that their proposed LSTM-RNN model outperforms state-of-the-art methods and LSTM unit also obtains the best performance compared to standard RNN and gated recurrent unit (GRU). [4]

In 2019, **Z. Wang, C. Wu, K. Zheng, X. Niu and X. Wang** present a personality prediction method based on particle swarm optimization (PSO) and synthetic minority oversampling technique+Tomek Link (SMOTETomek)resampling (PSO-SMOTETomek), which, apart from effective SMOTETomek resampling of data samples, is able to execute PSO feature optimization for each set of feature combinations. Validated by simulation, our analysis reveals that the PSO-SMOTETomek method is efficient under a small dataset, and the accuracy of personality recognition is improved by up to around 10%. The results are better than those of previous similar studies. The average accuracies of the plain text dataset and the non-plain text dataset are 75.34% and 78.78%, respectively. The average accuracies of the short text dataset and the long text dataset are 75.34% and 64.25%, respectively. From the experimental results, we found that short text has a better classification effect than long text. Plain text data can still have high personality discrimination accuracy, but there is no relevant external information. The proposed model is able to facilitate the design and implementation of a personality recognition system, and the model significantly outperforms existing state-of-the-art models. [5]

III. METHODOLOGY

The proposed methodology is depicted diagrammatically in figure 1. The steps involved in the proposed system is as follows, the data set for drug review is taken from the UCI Machine Learning Repository. This dataset provides patient ratings for specific medications along with associated medical conditions and a 10-star rating that reflects overall patient satisfaction. Features such as the patient rating of the drug, patient condition, name of the drug, date of use, and a number of useful users, which indicate the number of users who found the review useful. This dataset contains several types of properties that are categorical, numeric, text, and date. Sentiment analysis is the main goal where we have to classify a review as positive or negative. The train and the test suite are first merged because the main goal is sentiment analysis. The opinion of the review is given according to the rating, as the opinion of the reviews is not initially included in the data set. Feature extraction is done to get a good perspective of the reviews to make good predictions. The pre-processing serves to prepare the data for further processing. The data set is then divided into training and test data sets. 80% of the data is used for training and the remaining 20% of the data is used for testing.

Figure 3.1 Proposed Methodology



Different machine learning classification algorithms which areare Naïve Bayes, SVM (Support Vector Machine), Logistic Regression, Decision Tree Classifier, SGD (Stochastic Gradient Descent) Classifier. And based on the Accuracy of algorithms and correct prediction we use Naïve Bayes and SVM (Support Vector Machine) algorithm to predict whether the drug can be used or not.

Table 1 and figure 2 show the total number of 10-star ratings for the drug. Totally there were 215063 reviews after data pre-processing it has become 213869.

1	2	3	4	5	6	7	8	9	10
28769	9203	8662	6622	10650	8403	12470	24909	36499	67682

Table 1: User Ratings(1-10scale)

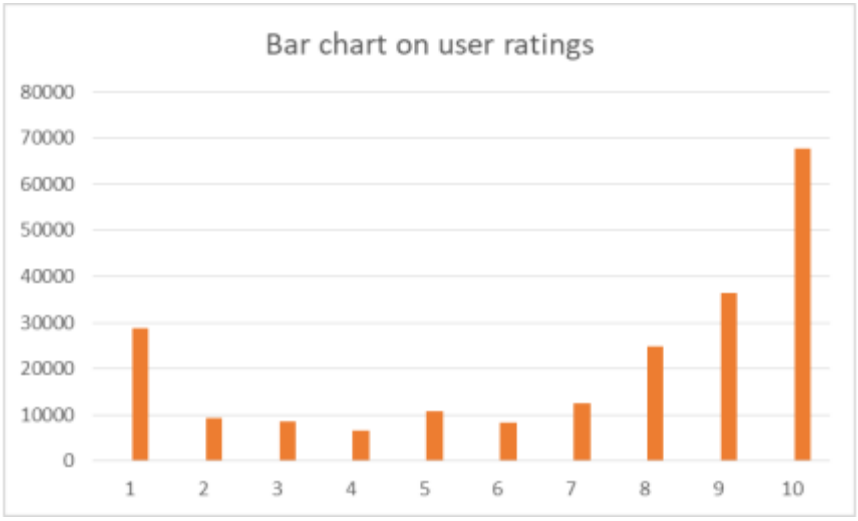


Figure 3.2 Bar chart on User ratings (1-10)

The ratings are converted into positive and negative sentiment by using the review polarity and it is converted using the condition >=5 as positive and<5 rating as negative. Table 2 shows the total positive and negative ratings.

User Ratings	
Positive	161491
Negative	53572

Table 2: User ratings after repalacement

IV. RESULTS

The classification report for the Naïve bayes model is given below (Table 4.1). It can be seen that the accuracy for predicting negative mood is 0.70 and for positive mood, it is 0.80. The biggest difference is their recall value, i.e., 0.68 for negative sentiment and 0.80 for positive sentiment. The accuracy of Naïve Bayes is 75.94007341998214.

Naïve Bayes Accuracy
The Accuracy of the model is : 75.94007341998214
The confusion matrix is

	precision	recall	f1-score	support
0	0.70	0.68	0.69	3944
1	0.80	0.81	0.80	6135
accuracy			0.76	10079
macro avg	0.75	0.75	0.75	10079
weighted avg	0.76	0.76	0.76	10079

Table 4.1: Classification report on Naïve Bayes

The classification report for the SVM model is given below (Table 4.2). It can be seen that the accuracy for predicting negative mood is 0.71 and for positive mood, it is 0.82. The biggest difference is their recall value, i.e., 0.72 for negative sentiment and 0.82 for positive sentiment. The accuracy of SVM is 77.69620001984325

SVM Accuracy
The Accuracy of the model is : 77.69620001984325
The confusion matrix is

	precision	recall	f1-score	support
0	0.71	0.72	0.72	3944
1	0.82	0.82	0.82	6135
accuracy			0.78	10079
macro avg	0.77	0.77	0.77	10079

weighted avg 0.78 0.78 0.78 10079

Table 4.2: Classification report on SVM

The classification report for the Logistic Regression model is given below (Table 4.3). It can be seen that the accuracy for predicting negative mood is 0.73 and for positive mood, it is 0.83. The biggest difference is their recall value, i.e., 0.73 for negative sentiment and 0.83 for positive sentiment. The accuracy of Logistic Regression is 78.72804841750174

Logistic Regression Accuracy

The Accuracy of the model is : 78.72804841750174

The confusion matrix is

precision recall f1-score support

0 0.73 0.73 0.73 3944

1 0.83 0.83 0.83 6135

accuracy 0.79 10079

macro avg 0.78 0.78 0.78 10079

weighted avg 0.79 0.79 0.79 10079

Table 4.3: Classification report on Logistic Regression

The classification report for the Decision Tree Classifier model is given below (Table 4.4). It can be seen that the accuracy for predicting negative mood is 0.63 and for positive mood, it is 0.76. The biggest difference is their recall value, i.e., 0.62 for negative sentiment and 0.76 for positive sentiment. The accuracy of Decision Tree Classifier is 70.63200714356583

Decision Tree Classifier Accuracy

The Accuracy of the model is : 70.63200714356583

The confusion matrix is

precision recall f1-score support

0 0.63 0.62 0.62 3944

1 0.76 0.76 0.76 6135

accuracy 0.71 10079

macro avg 0.69 0.69 0.69 10079

weighted avg 0.71 0.71 0.71 10079

Table 4.4: Classification report on Decision Tree Classifier

The classification report for the SGD Classifier model is given below (Table 4.5). It can be seen that the accuracy for predicting negative mood is 0.74 and for positive mood, it is 0.82. The biggest difference is their recall value, i.e., 0.71 for negative sentiment and 0.84 for positive sentiment. The accuracy of SGD Classifier is 79.1546780434567.

SGD Classifier Accuracy

The Accuracy of the model is : 79.1546780434567

The confusion matrix is

precision recall f1-score support

0 0.74 0.71 0.73 3944

1 0.82 0.84 0.83 6135

accuracy 0.79 10079

macro avg 0.78 0.78 0.78 10079

weighted avg 0.79 0.79 0.79 10079

Table 4.5: Classification report on SGD Classifier

V. CONCLUSION AND FUTURE SCOPE

Reviews are becoming integral part of our lives. Whenever we purchase something online, we first check reviews to decide whether to buy that thing or not. In this proposed system, we are building a drug recommendation system in which based on the reviews we can decide whether the drug can be used or not. We first train the model by using five algorithms which areare Naïve Bayes, SVM (Support Vector Machine), Logistic Regression, Decision Tree Classifier, SGD (Stochastic Gradient Descent) Classifier. And based on the Accuracy of algorithms and correct prediction Naïve Bayes and SVM (Support Vector Machine) algorithms are used to predict whether the drug can be used or not. If the model results review as positive, then the drug is safe to be used and if the model results review as negative then the drug is not safe to be used.Advantagesof this system is that this 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 and the system has exact sentiment analysis prediction techniques for Data Cleaning and Visualization. Disadvantages of this

system is that this system cannot be used to predict drugs for severe diseases as the collection of information of such diseases is not so easy.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.

REFERENCES

[1]. Zhang, Yin & Zhang, Dafang & Hassan, Mohammad & Alamri, Atif & Peng, Limei. (2014). CADRE: Cloud-Assisted Drug Recommendation Service for Online Pharmacies. Mobile Networks and Applications. 20. 348-355. 10.1007/s11036-014-0537-4.

[2]. Danushka Bollegala, Takanori Maehara and Kenichi Kawarabayashi. Unsupervised Cross-Domain Word Representation Learning, 2015; arXiv:1505.07184.

[3]. Y. Bao and X. Jiang," An intelligent medicine recommender system framework," 2016 IEEE 11th Conference on Industrial Electronics and Applications (ICIEA), Hefei, 2016, pp. 1383-1388, doi: 10.1109/ICIEA.2016.7603801.

[4]. J. Li, H. Xu, X. He, J. Deng and X. Sun," Tweet modeling with LSTM recurrent neural networks for hashtag recommendation," 2016 International Joint Conference on Neural Networks(IJCNN),Vancouver,BC,2016,pp.15701577,doi:10.1109/IJCNN.2016.7727385.

[5]. Z. Wang, C. Wu, K. Zheng, X. Niu and X. Wang, "SMOTETomek- Based Resampling for Personality Recognition," in IEEE Access, vol. 7, pp. 129678-129689, 2019, doi: 10.1109/ACCESS.2019.2940061.