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Drugs Rating Generation and Recommendation from Sentiment Analysis of Drug Reviews using Machine Learning

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ABSTRACT

As a result of all of this complex information, the user can benefit from a recommendation system by forming an awareness of their needs and making well-informed judgments. User-generated material is portrayed using human language in a variety of ways, making it difficult to make recommendations based on sentiment analysis. Health and medicine have received much too little attention in research, which has tended to concentrate on more mundane topics like product reviews for electronics, movies, and dining establishments. To improve public health and make the right decision, it may be necessary to do a sentiment analysis of healthcare in general and the drug experiences of individuals in particular. Design and implementation of a drug recommendation system that uses sentiment analysis technologies on drug reviews are presented in this study. The goal of this study is to create a decision-support platform that will assist patients in making more informed decisions about their pharmacological treatment options.

Keywords: hybrid, TF–IDF, Knowledge-Based,

I. INTRODUCTION:

Social media is a term that refers to the huge amounts of content created by users on Web 2.0 platforms, such as Facebook and Twitter. Consequently, during the last decade, an excessive number of academics have been working to develop algorithms that can accurately detect sentiment in user-generated content [1]. Opinion mining, another name for sentiment analysis, is the study of people's thoughts, feelings, and impressions about a wide range of things, such as products, services, organisations, individuals, and events. These two areas of application have seen a lot of attention in the last few years.

There are two types of analyses in sentimental research: positive and negative. However, if all contenders' items evoke pleasant or negative sensations, it becomes difficult for individuals to make a decision.. People need to know not only if the product is nice but also how good it is in order to make a decision. According to some, people prefer distinct ways of expressing their emotions [2]. As a result, in many real-world situations, such as prescription recommendations, numerical scores are preferable to binary selections, and systems of decision support are needed to help consumers make product choices. There are both obstacles and opportunities in this new application arena for medical health.

The goal of a recommendation framework is to forecast the preferences of users and generate recommendations that are relevant to them [1]. Traditional recommendation technology (RT) concludes collaborative filtering (CF), content-based (CB), knowledge-based (KB), and hybrid recommendation technologies [3]. CB's recommendations are overly narrow, whereas CF's sparsity, scalability, and cold-start difficulty are serious drawbacks. The sentiment analysis of healthcare in general and the user's drug experience, in particular, can shed significant light on the process of improving public health and making the right decisions, according to some researchers [4], [5]. This system combined with traditional recommendation systems is more effective.

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1.1 Recommendations for drug use

One of the most significant and difficult jobs in today's world is making drug recommendations. Doctors have identified a wide range of new ailments. The adverse effects of a drug for one condition may lead to the identification of additional diseases in the future. Doctors and patients alike will benefit from our effort to create a recommendation model that will help doctors prescribe the right medication even if they haven't studied about it before. The model will also help inexperienced doctors and patients by providing them with the information they need in order to prescribe the right medication. A recommender system's accuracy and efficiency must be extremely high.

1.2 Machine Learning for Prescription Drug Suggestions

Patients' health conditions, demographic goals, and the pharmaceuticals needed to treat them are all generated by the rising healthcare sector. Medical doctors and data scientists alike are interested in them. A machine learning and natural language processing-based drug recommendation assistance. It draws its accuracy from a variety of large datasets. An individual's "effectiveness" can be determined using the system's contrasting effects, reviews, and ratings, and the system then recommends the best drug for that individual.

We are interested in opinion mining in drug reviews, where people contribute their experiences and ideas about medicines and then classify the comments into ratings and even offer a prescription list that would be most appropriate for the patient. In addition to helping patients, pharmacists and physicians will benefit from implementing the proposed approach to sentiment analysis because it provides relevant public opinion summaries.

Nowadays, many people choose to purchase medical supplies online rather than wait in long lines at the hospital for an appointment with a doctor. 1.4 Problem Statement They rely heavily on the opinions of other patients who have used the medication in the past or who have the same problem as they do. While this medication may not cause negative effects in men, it may cause side effects in women.

Corona virus is one such disease that is attacking the human world today and necessitates many medical systems and medical human experts, both of which are in short supply due to the rise in the number of diseases and the resulting need for patients to take medications at their own risk, potentially resulting in death or serious injury to the patient's body.

This study introduces a sentiment and machine learning based drug recommendation system that accepts disease names from patients and then recommends a drug and displays a SENTIMENT rating based on reviews from previous users. As long as the projected rating is high, a patient can put their trust in the drug and take it.

II. Contribution to the field of study:

To extract features from a text, the author of the proposed paper used various algorithms, including TF-IDF (term frequency – inverse document frequency), BAG of WORDS and WORVEC, and these extracted features will be applied to various machine learning algorithms, including Logistic Regression and Linear SVC. TF-IDF is the best method out of all of them, thus we're using it to extract features from the data.

2.1 Proposal for a new computer system

As a solution to the current dilemma, the author of this work introduces a sentiment and machine learning based medicine recommendation system that would accept disease names from patients and then offer drugs and display sentiment ratings from previous users. Predicted ratings are a good indicator of how likely it is that a patient would take a prescribed medication.

III. Algorithms

Machine learning algorithms such as Logistic Regression, Linear SVC, Ridge classifier, Nave Bayes, Multilayer Perceptron classifier, and SGD classifier are used in this research..

3.1 SVC linear

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For a linear SVC (Support Vector Classifier), the primary goal of fitting the data you provide is to generate a "best fit" hyperplane that divides (or categorises) our dataset. Our classifier can then use the hyperplane to determine the "predicted" classification by feeding it certain features.

3.2 Regression Analysis 3.2 Logistic

The model creates a regression model to predict the likelihood that a given data entry falls into the "1" category.

3.3 Regression of the ridge

When using the Ridge Classifier, the label data is transformed into [-1, 1] and the regression method is used to resolve the issue.

The SGD Classifier is the 3.4 version (Stochastic Gradient Descent)

The SGD classifier is an effective and simple method for classifying huge datasets.

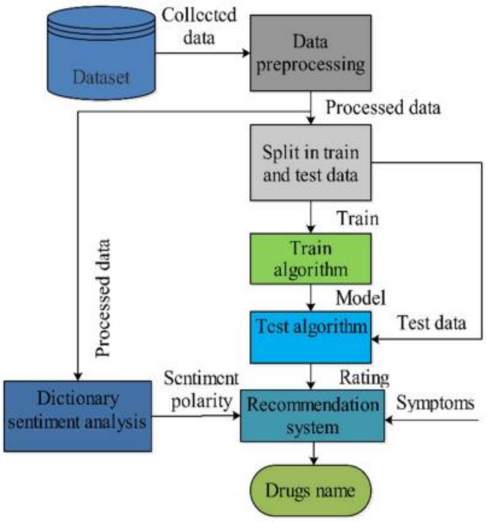

Fig.1. Architecture/Framework

3.4 Algorithm and Process Design:

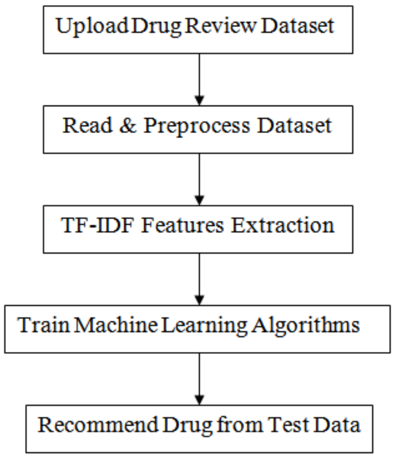

Fig.2. Process Design

Step I First, Use this module to upload a dataset for use in the drug review process.

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This module reads and preprocesses the dataset, extracting the reviews, medicine names and ratings and forming a features array.

Step II. Second, the TF-IDF technique will be used to discover the average frequency of each word and replace that word with the frequency value to produce a vector. If a word is missing from the statement, a 0 will be entered instead. Machine learning algorithms will use all reviews as input features, and RATINGS and the name of the drug will be used as class labels.

In this module, we will use TF-IDF features to train all machine learning algorithms, and then apply this model on test data to calculate the algorithm's prediction accuracy.

Strep III We'll use this module to create a comparison chart showing the accuracy of each method.

When we use this module, machine learning (ML) predicts the name and rating of a medicine based on the test data we provide.

Step IV: Put into Practice and Evaluate

IV. Compilation of data

4.1 Dataset

We used the DRUGREVIEW dataset from the UCI machine learning website to implement this project, and the dataset diagram shots are shown below.

This graphic shows dataset column titles like "drug name," "condition," "review," and "rating," as well as dataset values. We'll utilise the above REVIEWS and RATINGS to train machine learning models, while the remaining rows show dataset values as shown. Machine learning will predict the name of the drug and its rating based on the data below.

Machine learning will be used to estimate drug ratings and names based on the disease name solely provided in the above test data.

4.2 Metrics for evaluating the performance of a product:

Our models are assessed using F1-Score, Accuracy, and Receiver Operating Characteristics-Area Under the Curve (ROC-AUC) metrics. FPR=False Positive Rate must be used to evaluate the F1-score, accuracy, precision, and recall.

A TPR is a true positive rate.

F1-score: Accuracy, Precision, Recall

True positive (TP) is defined as the number of events that were correctly identified.

A false negative (FN) is the number of events mistakenly anticipated and not necessary, while a false-positive (FP) is the number of events that were incorrectly predicted.

The percentage of false positives: Machine learning accuracy can be assessed using this statistic.. In layman's terms, FPR=FP/(FP+TN)

TPR is defined as TPR=FP/(FP+TN) because it is a synonym for recall.

The most essential performance indicator is accuracy, which can be calculated simply by dividing the total number of observations by the number of properly predicted observations.

Accuracy=(TN+TP)/(TP+FP+TN+FN)

In the original data, it is the ratio that properly predicts positive observations out of all of the original observations.

To recap, recall is equal to TP divided by (TP plus FN).

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In order to get the most accurate results, precision is needed. In other words, this means determining the total number of predicted positive softwares from the total expected positive softwares. Precision is defined as TP/(TP + FP) = TP/(TP + FP)

F1-score: The F-score is a technique of integrating precision and recall in a machine learning model. It is defined as the harmonic mean of the model's precision and recall https://deepai.org/machine learning glossary terms/precision and recall. In the context of machine learning, "harmonic mean" is a word that describes the accuracy and recall of a model's predictions. The F-score is another name for it. The F1 score is defined as 2(Precision Recall/Precision + Recall) = F1 Score.

The area under the ROC-AUC curve using prediction scores is used to produce the ROC-AUC, another useful statistic for classifying situations.

4.3 The final result is:

You can receive the following diagram by clicking 'Upload Drug Review Dataset' in the above diagram.

Selecting and uploading the DRUG dataset is shown in the picture above, and clicking the 'Open' button loads the dataset and produces the diagram below.

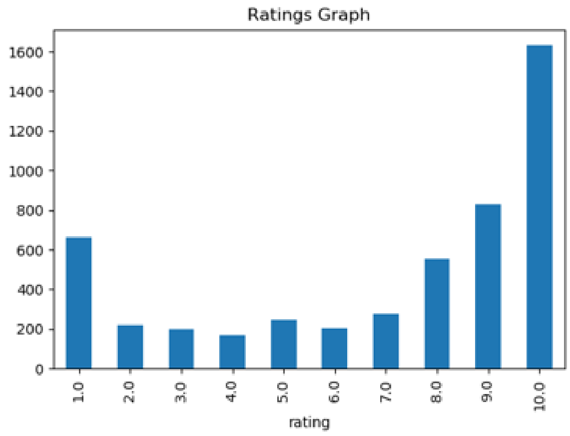

Fig.3.Rating Graph

An x-axis shows ratings, and a y-axis shows how many records received that rating. The data is shown in the graph above. Now that the graph has been closed, click on the 'Read & Preprocess Dataset' button to read all dataset values and then preprocess to remove stop words and special symbols, and finally construct a features array..

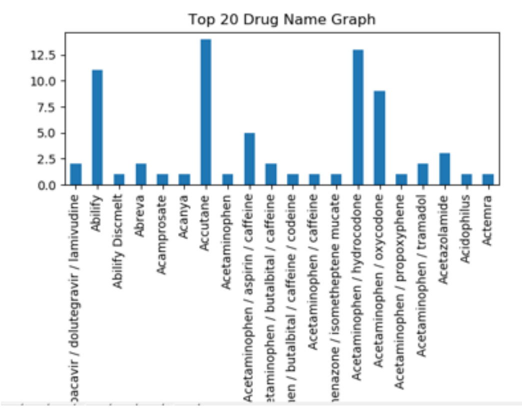

Fig.4.Drug name graph

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All reviews had stop words and special symbols deleted from the dataset, and in the graph I'm exhibiting my top 20 drugs, which are based on this dataset. The x-axis is the drug name, and the y-axis is the number of times the medicine has been used. Simply click 'TF-IDF Features Extraction' to extract the average frequency of all the reviews and then close the previous graph.

```
      abilify able abnormal absolutely ache acne active ... yeast yes yesterday yet  yr zero zoloft
0         0.0  0.0      0.0        0.0  0.0  0.0    0.0 ...   0.0 0.0       0.0 0.0 0.0  0.0    0.0
1         0.0  0.0      0.0        0.0  0.0  0.0    0.0 ...   0.0 0.0       0.0 0.0 0.0  0.0    0.0
2         0.0  0.0      0.0        0.0  0.0  0.0    0.0 ...   0.0 0.0       0.0 0.0 0.0  0.0    0.0
3         0.0  0.0      0.0        0.0  0.0  0.0    0.0 ...   0.0 0.0       0.0 0.0 0.0  0.0    0.0
4         0.0  0.0      0.0        0.0  0.0  0.0    0.0 ...   0.0 0.0       0.0 0.0 0.0  0.0    0.0
...       ...  ...      ...        ...  ...  ...    ... ...   ... ...       ... ... ...  ...    ...
4995      0.0  0.0      0.0        0.0  0.0  0.0    0.0 ...   0.0 0.0       0.0 0.0 0.0  0.0    0.0
4996      0.0  0.0      0.0        0.0  0.0  0.0    0.0 ...   0.0 0.0       0.0 0.0 0.0  0.0    0.0
4997      0.0  0.0      0.0        0.0  0.0  0.0    0.0 ...   0.0 0.0       0.0 0.0 0.0  0.0    0.0
4998      0.0  0.0      0.0        0.0  0.0  0.0    0.0 ...   0.0 0.0       0.0 0.0 0.0  0.0    0.0
4999      0.0  0.0      0.0        0.0  0.0  0.0    0.0 ...   0.0 0.0       0.0 0.0 0.0  0.0    0.0

[5000 rows x 700 columns]

[0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.
 0.    0.    0.    0.    0.    0.
```

Fig.5. TF-IDF vector

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 diagram to view some non-zero frequency values

```
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        5.75599308 0.       0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
2.29171172 0.       0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
0.        0.        0.        0.        0.        0.
```

Fig.6. non-zero average frequency values

In above diagram 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

```
Logistic Regression Precision  : 80.54683467044312
Logistic Regression Recall     : 79.30203003457763
Logistic Regression F1-Score   : 79.72928850771024
Logistic Regression Accuracy   : 76.0

Linear SVC Precision  : 70.51855963732795
Linear SVC Recall     : 71.1815169715316
Linear SVC F1-Score   : 70.46290195776827
Linear SVC Accuracy   : 67.80000000000001

Ridge Classifier Precision  : 66.78687974483705
Ridge Classifier Recall     : 37.72383152495436
Ridge Classifier F1-Score   : 42.784203316921044
Ridge Classifier Accuracy   : 55.1

Multinomial Naive Bayes Precision  : 41.32611772759363
Multinomial Naive Bayes Recall     : 47.984631801286945
Multinomial Naive Bayes F1-Score   : 43.14147322230588
Multinomial Naive Bayes Accuracy   : 47.199999999999996
```

Fig.7. accuracy, precision, recall and FSCORE

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In above diagram for each algorithm we calculate accuracy, precision, recall and FSCORE and in all algorithms MLP has got high performance and now click on 'Comparison Graph' button to get below graph

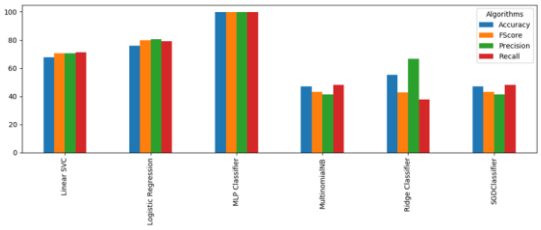

Fig.8. Accuracy

Each colour bar indicates a distinct statistic, and the above graph shows that MLP has excellent performance. The x-axis represents the algorithm name, and the y-axis represents accuracy, precision recall, and FSCORE. Afterwards, shut the graph above and then click on the 'Recommend Medicine from Test Data' button to submit test data and get anticipated results as a drug name and rating.

Prediction results are shown below after selecting and uploading 'testData.csv' in the diagram above and then clicking the 'Open' button.

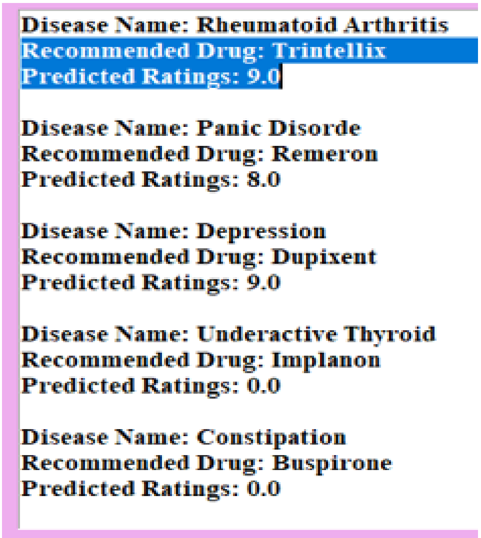

Fig.9. predict recommended drug name and ratings

In the figure above, the names and ratings of suggested drugs for each type of condition are depicted.

The following are the expected outcomes of the extension:

However, because the majority of people in Telangana/AP state are fluent in Telugu, we're adapting our programme to display suggested drug output in either English or Telugu, depending on the user's preference, as an extension of this project's user reviews for recommended pharmaceuticals. If the user selects Telugu, the recommended drugs will be displayed in Telugu, however if they select English, they will be displayed in English.

Run all the buttons in the graphic above, and if you want to get recommended drugs in Telugu, then pick Telugu from the drop-down box and then click on the 'Recommend Drug from Test Data' button to upload test data and get anticipated result as Telugu.

As seen in the diagram above, I selected Telugu as the language from the drop-down box before clicking 'Recommend Drug from Test Data' to upload 'testData.csv,' and then clicked 'Open,' to submit the test data, resulting in the outcome shown below.

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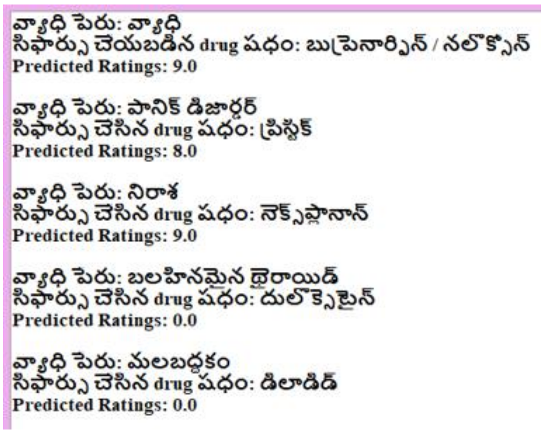

Fig.10. output as Telugu and by selecting English

In above diagram we got recommended output as Telugu and by selecting English we can get output like below diagram in English

Fig.11. recommended output as English

Extensions can be used to present user-recommended output in both English and Telugu, as seen in this diagram.

CONCLUSION

To extract features from a text, the author of the proposed paper used various algorithms, including TF-IDF (term frequency – inverse document frequency), BAG of WORDS and WORVEC, and these extracted features will be applied to various machine learning algorithms, including Logistic Regression and Linear SVC. As an extension work, we're converting an application to display recommended drug output as ENGLISH or Telugu based on user selected option when TF-IDF has the best performance among all algorithms. However, in Telangana/AP state most people are familiar with Telugu language but propose paper recommending drugs only in English.

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