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DRUG RATING GENERATION AND RECOMMENDATION FROM SENTIMENT ANALYSIS OF DRUG REVIEWS USING MACHINE LEARNING

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Abstract: A recommendation system helps the user understand needs and provides guidelines when making decisions out of a sea of confusing information. Since that user-generated data is expressed in a variety of complex ways using human language, generating suggestions from a study of attitudes appears to be a challenging task. Healthcare sentiment analysis is less focused on making informed judgments and less engaged in raising the bar for public health. In this project, we create and put into use a drug recommendation system that analyses drug reviews using sentiment analysis technology. The goal of this research is to create a system for making decisions that will enable patients to choose from a vast array of medications. In the initial stage of our development, we provide an approach to sentimental measurement for medicine reviews and offer ratings on medications. In addition, we analyse the dictionary sentiment, polarity of medicine reviews, patient conditions, and how accurate the reviews are useful to users. Next, to identify suitable drugs, we incorporate those variables into the recommendation algorithm. Convolution neural networks have been tested in experiments for recommendation based on the provided open dataset. To increase performance, analysis is done to fine-tune the settings for each method. In order to achieve good trade-offs between model accuracy, model efficiency, and model scalability, Linear Support Vector Classifier is improved in rating generation.

Index Terms **– Drug Recommendation.**

I. INTRODUCTION

The drugs are recommended for the patient automatically after comprehensively considering each symptom. We use user drug reviews into Decision Tree, KNN, and Linear SVC machine learning algorithms to achieve the rating generation task. Tuning the various parameters, we have tried to increase the accuracy of the rating generation. We compared the algorithms and all of them have different performances concerning the prediction accuracy. Finally, the Linear SVC model is selected for rating generation to obtain a good tradeoff among model accuracy (83.0%), model efficiency, and model scalability. Then take this result in Hybrid Recommendation Model to list appropriate medications. Besides, we conducted the emotional analysis using an emotional word dictionary to overcome limitations of a package formed with movie data. The results of this study show that the sentimental attributes contribute greatly to the prediction of drug rating, as well as recommendations. It also demonstrates significant improvements on a real-world dataset compared to current strategies. In our proposed work, when evaluating the context, we can find more linguistic rules, and to incorporate phrase-level sentiment analysis, we may adapt or build hybrid factorization models such as tensor factorization, or deep learning techniques. We also plan to enhance the accuracy and reliability of the recommendation model further.

1.1 Scope: "Prediction of Drugs in Sentiment Analysis Using Machine Learning Techniques" computer vision is one the applications of convolution neural networks that enables us to automate tasks that earlier required years of expertise and one such use in predicting the presence of disease cells.

1.2 Objective: The objective of this research is to build a decision-making support platform to help patients to achieve more significant choices in drug selection.

1.3 Basic Concepts

Machine Learning: Machine learning (ML) is the study of computer algorithms that improve automatically through experience. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data" in order to make predictions or decisions without being explicitly programmed to do so.

Supervised classification: Supervised classification is based on the idea that a user can select sample pixels in an image that are

representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image. Training sites(also known as testing sets or input classes) are selected based on the knowledge of the user.

Unsupervised classification: Unsupervised classification is where the outcomes (groupings of pixels with common characteristics) are based on the software analysis of an image without the user providing sample classes. The computer uses techniques to determine which pixels are relate and groups the min to classes. The user can specify which algorithm the software will use and the desired

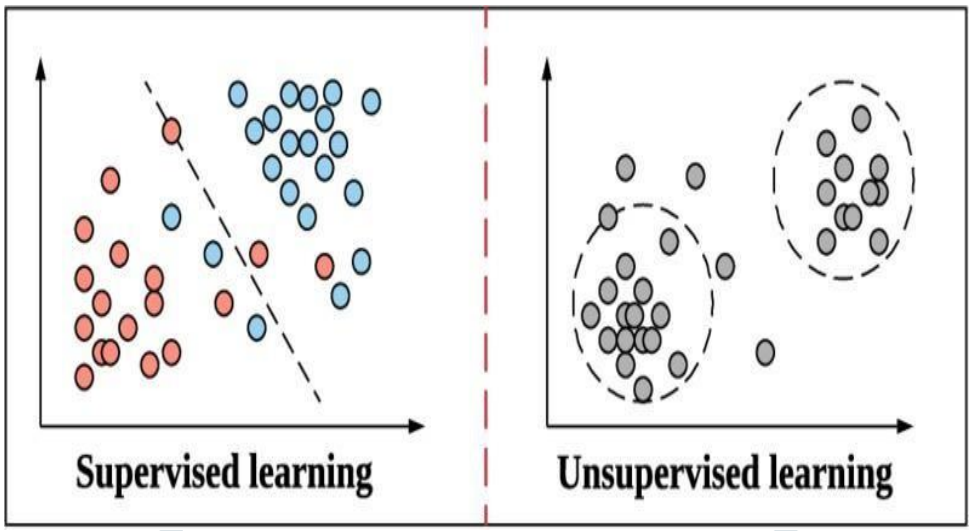

Fig 1.1 Types of Machine Learning

Feature Extraction: Feature extraction involves reducing the number of resources required to describe a large set of data. When performing analysis of complex data one of the major problem's stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm over fit to training samples and generalize poorly to new samples.

II. LITERATURE SURVEY

Recommendations techniques aim to provide consumers with personalized goods and services to cope with the growing issue of overloading online information. Studies used numerous methods for sentiment analysis, and since the mid1990s, recommender model strategies have been recommended. Many early researches concentrate on document-level study and refer to e-business, e-government, e-learning, e-commerce/e shopping, e-tourism, etc. However, the world of medicine contains rare recommending technologies. Mohammad Ehsan Basiri at el. suggest two deep fusion models for evaluating drug reviews focused on 3-way decision theory. The first fusion model, a 3-way fusion of a single deep model with a traditional training algorithm (3W1DT), was developed as a primary classifier using a deep learning method and a traditional learning process as a secondary method employed when there is weak trust in the deep method during the labeling of test samples.

The 3-way fusion of three deep models including a traditional model (3W3DT), three deep and a traditional model is learned over the whole training data in the second suggested deep fusion model and each classifies the test sample uniquely. Then to categorize the test drug review, the most assured classifier is chosen. Sairamvinay Vijaya raghavan at el. decided to evaluate reviews of different medications that were analyzed in the form of texts and were also given a ranking on a scale of 110. In general, they divided the drug number rating into three classes: negative (1-4), neutral (4-7) or positive (7-10). For the medications that belong to the comparable condition, there are many reports and they wanted to examine how various terms are used by the reviews for different conditions to influence the drug ratings. Their goal was primarily to introduce supervised machine learning classification algorithms that use textual review to determine the class of the ranking. Various features, such as Term Frequency Inverse Document Frequency (TFIDF) as well as Count Vectors (CV), were primarily performed. In the data collection, they had learned models on the most common factors, such as 'Depression', 'Birth Control' and 'Pain'.

Vikrant Doma at el. introduced a drug recommendation assistant, constructed using machine learning methods as well as natural language processing, which generates its accuracy with several major datasets. The introduced method allows the contrasting effects, feedback, rankings, to be manifested and then recommends the most "effective"medication for a given person. The findings of the predictive study found that the death rates of the top deadliest diseases in the U.S. all rose significantly between 2005 and 2015, between the ages of 55 and 80. The next top five medical conditions (depression, birth control, pain, acne, anxiety), which will be widespread in the near future and the five medications used to treat them, can be predicted with some degree of precision based on the existing trends. Ahmed Abdeen Hamed at el. are launching their initial work to build a recommendation scheme for social networks called T-Recs.The system is a time-aware alternative medicine recommendation system based on Twitter. For three consecutive weeks, they compiled a collection of tweets containing unique hash tags (#throwing up, #headache, #itching,etc.) (about 500,000 tweets).

The individual tweets were manually reviewed by a domain expert (a medical doctor) who examined the feelings of the tweet along with the timestamp of the tweet. The domain expert assigned the tweet/group of tweets a preliminary label using this knowledge. Authors then trained a classifier (Decision Tree algorithm) using the hash tags and their labels, taking into account other variables (i.e. age, gender, conditions of co morbidity) that must be given by the Tweeter by taking a questionnaire. The recommender framework makes suggestions based on the contents of the tweet and the questionnaire factors for never-seen-before tweets after the questions are answered. Chun Chen at el. use actual medical online cases and carry out large-scale data

processing and build an Implicit Drug Recommendation Feedback and Crossing Recommendation (IFCR) framework then support doctors in drug choice.

The new platform is intended to examine epileptics' psychiatric records in order to determine the relationship between the syndromes and the medications. The authors studied two recommendation algorithms and developed an ensemble model that merged IFCR with ANN to maximize their respective advantages in drug recommendation. Rahul Majethia at el. This helps to eliminate certain drugs, which would almost certainly have an adverse effect on the health of the patient and thus obtain a set of recommended drugs. Chen et al. provide a context-based, personalized antihypertensive drug recommendation system , and develop a contextual support framework. They suggest a guidance framework focused on domain-ontology for diabetes medication. The software builds ontological awareness of each patient's condition regarding the essence of the medication as well as the nature of distribution and health risks, and also apply Semantic Web Rules Language (SWRL) and the Java Expert System Shell (JESS) to construct a possible patient preface. Alternatively, Gottlieb et al. suggest a clinical recommendation technique based on similarity.

Shimada et al. replace the medical recommendation method with a decision tree classifier algorithm that encourages decision-making by doctors and advises first-line (over prescription) care. With the exception of the earlier study, Zhang et al. define a hybrid recommendation structure that connects artificial neural networks with case-based reasoning. Diana Cabral and Ricardo B. C. Prudence developed a system for separating aspects and classifying them in drug reviews. The produced solution consists of two key phases. In the aspect extraction, a system focused on syntactic pathways of attachment is designed to extract opinion pairs in drug comments, composed of an aspect word paired with an emotion modifier. In order to classify the opinion pairs by aspect category (e.g., condition, adverse effect, dose, and efficacy), a supervised classification is established in aspect classification based on domain and linguistic tools.

III. System Analysis

3.1 Problem Definition

The drugs are recommended for the patient automatically after comprehensively considering each symptom. We use user drug reviews to achieve the rating generation task. Tuning the various parameters, we have tried to increase the accuracy of the rating generation. We compared the algorithms and all of them have different performances concerning the prediction accuracy. Finally, the Linear SVC model is selected for rating generation to obtain a good tradeoff among model accuracy (83.0%), model efficiency, and model scalability. Then take this result in Hybrid Recommendation Model to list appropriate medications. Besides, we conducted the emotional analysis using an emotional word dictionary to overcome limitations of a package formed with movie data. The results of this study show that the sentimental attributes contribute greatly to the prediction of drug rating, as well as recommendations. It also demonstrates significant improvements on a real-world dataset compared to current strategies. In our proposed work, when evaluating the context, we can find more linguistic rules, and to incorporate phrase-level sentiment analysis, we may adapt or build hybrid factorization models such as tensor factorization, or deep learning techniques. We also plan to enhance the accuracy and reliability of the recommendation model further.

3.2 Existing System

Recommendation from an analysis of sentiments seems to be a great challenge as user-generated content is represented using human language in several complicated ways. Many studies have focused on common fields such as reviews of electrical items, films, and restaurants, but not enough on health and medical issues. Sentiment analysis of healthcare in general and that of the drug experiences of individuals, in particular, may shed considerable light on how to focus on improving public health and reach the correct decision.

3.3 Proposed System

In propose system we used various features extraction algorithms such as TF-IDF (term frequency – inverse document frequency), BAG of WORDS and WORVEC and this extracted features will be applied on various machine learning algorithm such as Logistic Regression, Linear SVC, Ridge classifier, Naïve Bayes, Multilayer Perceptron classifier, SGD classifier. Among all algorithms TF-IDF is giving better performance so we are using TF-IDF features extraction algorithm with above mention algorithm.

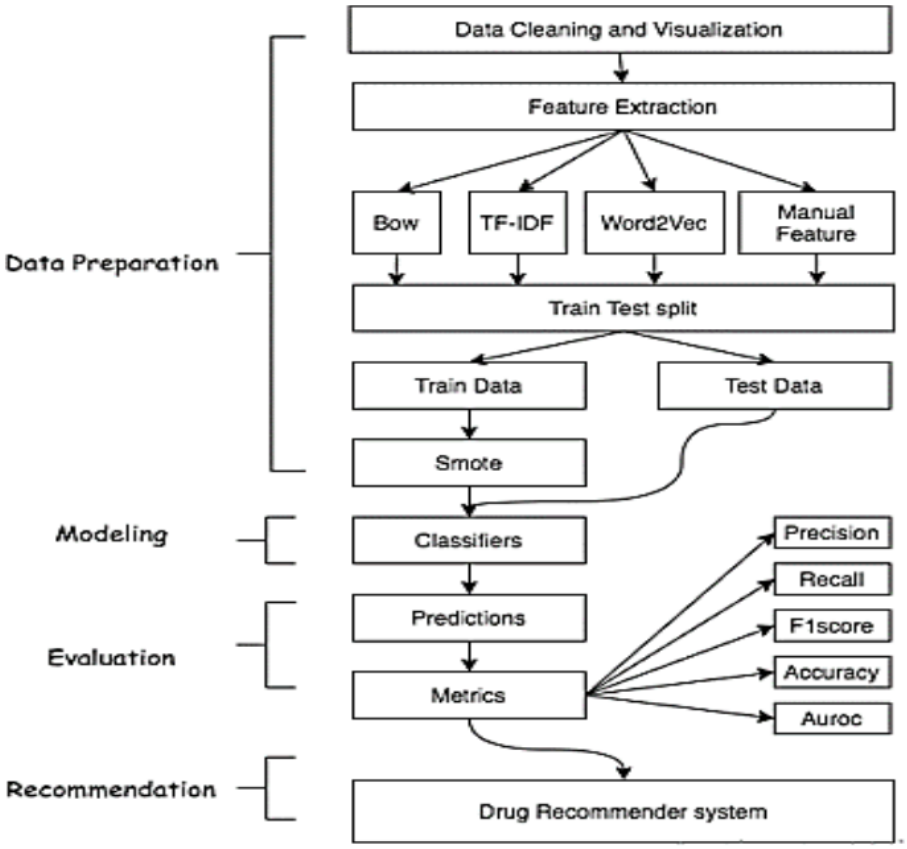

Fig 3.1 Architecture of Proposed Model

IV. System Implementation

4.1 Data pre-processing: Data cleaning is the method of finding and fixing (or removing) damaged or defective information from a record set, which refers to discovering missing, incorrect, defective, or irrelevant sections of the data and then adding, changing, or deleting dirty or coarse data. A collection of preprocessing steps needed to allow the machine learning system and algorithms to read and analyze the data, as well as to reduce the dataset to contain the necessary data points and attributes for the analysis. These are the following tools we used for preprocessing our drug dataset.

4.2 Tokenization: The process by which the running text is segmented into terms and phrases. The key task is to divide a text into tokens while throwing off other characters like dots.

4.3 Stop word: This approach filters out and omits some very common words that seem to offer little to no meaning to the NLP target. This excludes the generic terms which are not insightful about the relevant material.

4.4 Handling Negative Adjectives: The thing is to avoid the elimination of words in a given sentence that will wipe out relevant details and change the meaning. Under these conditions, we can pick a minimum to stop word lists or tests of this form (not good / not so good, not bad / not so poor) in our data under certain conditions and delete them from stop words.

4.5 Stemming: Refers to the slicing process of the end or beginning of words to remove affixes (lexical additions to the word's root).

4.6 Lemmatization: Has the purpose of reducing a word to its base form and of grouping various forms of the same word together.

4.7 Feature Extraction:

4.7.1 Unigrams: Every word in the pre-processed review corpus is taken into account as a feature in the unigrams model. As a result, developing a feature vector for a review is simple. First, it compiles a dictionary of all the words found in the analysis corpus. The next step is to construct a word-opinion matrix, where the arrival I j) represents the frequency of occurrence of word I in opinion j.

4.7.2 Unigrams & Bigrams: A technique for extracting features frequently utilized in the processing of natural languages is the unigrams model. Implementation is fairly straightforward and frequently produces astonishingly effective outcomes. The fact that it detaches each term, however, makes it difficult to recognize connections between pairs (such as a word and its suffix, a word and its negation, etc.). In order to account for the impact of adverbs like "good medicine" and "not bad," bigrams are being added to the unigram model. All 2-tuples of terms, or all pairs of subsequent words, that appear in the study's corpus are also included in the dictionary. The matrix is still calculated in the same manner, but it now includes additional rows. 6.7.3 Unigrams, Bigrams & Trigrams: To accurately reflect the impact of sentences like "not very good," we are now including trigrams (i.e., all triples of consecutive words) in the unigrams & bigrams model. However, keep in mind that the same trigram is rarely found in two papers

because it is improbable that two separate analysts would employ the same 3-word term. As a result, the results of this model should not significantly differ from those of the model of unigrams and bigrams.

4.8 Methodology:

4.8.1 Decision Tree (DT):

One of the most popular hierarchical models for supervised learning, which uses decision nodes in the test function to identify local regions as a sequence of recursive separations. The decision tree algorithm's logic is straightforward yet nevertheless highly effective. The 6 two subsections can then be separated again before the homogeneity or any other time-based pausing thresholds are met. This method divides data into two subsections to keep the information in each section quite homogeneous (all of the information in the section is of the same target class) than the prior/alternate subsections. The same predictor parameter can be applied over a larger decision tree. The ultimate aim of separation is to evaluate the correct variable correlated with the appropriate threshold to increase subgroup/branch homogeneity.

4.8.2 K-Nearest Neighbors (KNN):

KNN is incredibly simple to use while doing difficult classification jobs in its simplest form. Because the learning phase is inexperienced, the algorithm is slack. Instead, whenever a new data point or instance is classified, all data are used for training. KNN is a non-parametric learning technique, hence the underlying data are simple. As most real-world data do not adhere to theoretical presumptions like linear separateness, uniform distribution, etc., this is a highly helpful feature. This accurately estimates the variation between a single sample and each training sample. The data sample is then assigned to the category where the most K training dataset exist using the K nearest data samples.

4.8.3 Support Vector Machine (SVM):

The SVM concept is based on the Structural Risk Minimization principle of computational learning theory and is one of the most reliable and effective techniques used in machine learning. In this theory, data is evaluated and the boundaries of decisions are described by having hyper planes. In the case of input data that cannot be easily separated, it utilizes 4 kernel structures for classification tasks including linear, polynomial, radial based, and sigmoid functions by mapping the input data into high-dimensional feature space to allow the data to be conveniently separable. The hyper plane divides the text vectors of each class in a way that the distinction is held as large as possible.

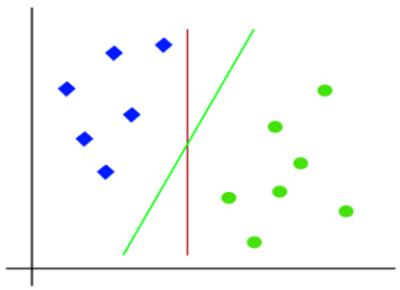

Fig 6.1 Support Vector Machine

VI. RESULTS AND DISCUSSION

Numerous classification algorithms were used to evaluate the reliability of the approaches for classifying sentiments, including Decision Tree, KNN, and Linear SVC. We split the data on the medications into two sections, consisting of 70% training data and 30% evaluation data. The overall accuracy rates, as well as per class accuracy rates for each model constructed from the test data samples are shown in Table 1, 2, and 3.

9.1 Result

Table 1: Classification result of Decision Tree

Class	Precision	Recall	F1-score
1	0.85	0.88	0.87
2	0.60	0.52	0.55
3	0.63	0.59	0.61
4	0.61	0.57	0.59
5	0.72	0.73	0.72

9.2 Discussion

Table 2: Classification result of KNN

Class	Precision	Recall	F1-score
1	0.55	1.00	0.71
2	0.77	0.01	0.01
3	0.77	0.02	0.04
4	0.86	0.02	0.04
5	0.73	0.00	0.00

Table 3: Classification result of LinearSVC

Class	Precision	Recall	F1-score
1	0.84	0.98	0.90
2	0.89	0.47	0.61
3	0.83	0.52	0.64
4	0.83	0.52	0.64
5	0.79	0.86	0.82

VII. Conclusion

This research work is doing correctly then the proposed method performs better than the other cited methods within the literature not only in achieving better accuracy, sensitivity, and specificity rates and also in terms of using a large data set of 1000 images for drug detection using machine learning techniques and also detect the drugs, we trained the external images and compared with other images to detect the drugs based on sentiment by using extract features. We have used different drug segmentation and nodules segmentation methods. Our work has consisted of preprocessing and drug segmentation by using thresholding, and also used the U-net model for detection of the candidate nodules of the drugs sentimental and classification methodology using CNN.

VIII. Future Enhancements

In our future work, when evaluating the context, we can find more linguistiques, and to incorporate phrase-level sentiment analysis, we may adapt or build hybrid factorization models such as tensor factorization, or deep learning techniques. We also plan to enhance the accuracy and reliability of the recommendation model further.

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