DRUG RECOMMENDATION SYSTEM BASED ON SENTIMENT ANALYSIS OF DRUG REVIEWS USING MACHINE LEARNING

Ms.V.R. Swetha[1], Pasam.Rajani[2]

[1]Assistant Professor, Dept of MCA, Audisankara College of Engineering & Technology (AUTONOMOUS), Gudur, AP, India.

[2]PG Scholar, Dept of MCA, Audisankara College of Engineering & Technology (AUTONOMOUS), Gudur, AP, India.

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 paper intends to present a drug recommender system that can drastically reduce specialists heap. In this research, we 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. The predicted sentiments were evaluated by precision, recall, f1score, accuracy, and AUC score. The results show that classifier LinearSVC using TF-IDF vectorization outperforms all other models with 93% accuracy.

I. INTRODUCTION

With the number of coronavirus cases growing exponent- tially, 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 top- level medication is significant for patients who need specialists that know wide-based information about microscopic organ- isms, 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 medi-cation 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.

This examination work separated into five segments: Intro- duction area which provides a short insight concerning the need of this research, Related works segment gives a concise insight regarding the previous examinations on this area of study, Methodology part includes the methods adopted in this research, The Result segment evaluates applied model results using various metrics, the Discussion section contains limita- tions of the framework, and lastly, the conclusion section.

II. LITERATURE SURVEY

With a sharp increment in AI advancement, there has been an exertion in applying machine learning and deep learning strategies to recommender frameworks. These days, recom- mender frameworks are very regular in the travel industry, e-commerce, restaurant, and so forth. Unfortunately, there are a limited number of studies available in the field of drug proposal framework utilizing sentiment analysis on the grounds that the medication reviews are substantially more intricate to analyze as it incorporates clinical wordings like infection names, reactions, a synthetic name that used in the production of the drug [8].

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, sensitivi- ties, and drug interactions. For empowering GalenOWL, clin- ical 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 al-gorithms, 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 bound- aries - 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 cloud- assisted drug proposal (CADRE). As per patients' side effects, CADRE can suggest drugs with top-N related prescriptions. This proposed framework was initially founded on collabora- tive filtering techniques in which the medications are initially bunched into clusters as indicated by the functional description data. However, after considering its weaknesses like com- putationally 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 anal-ysis, Jiugang Li et al. [15] constructed a hashtag recommender framework that utilizes the skip-gram model and applied con- volutional 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 explo- ration 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 WORK

The dataset used in this research is Drug Review Dataset (Drugs.com) taken from the UCI ML repository [4]. This dataset contains six attributes, name of drug used (text), review (text) of a patient, condition (text) of a patient, useful count (numerical) which suggest the number of individuals who found the review helpful, date (date) of review entry, and a 10-star patient rating (numerical) determining overall patient contentment. It contains a total of 215063 instances.

Fig. 1 shows the proposed model used to build a medicine recommender system. It contains four stages, specifically, Data preparation, classification, evaluation, and Recommendation.

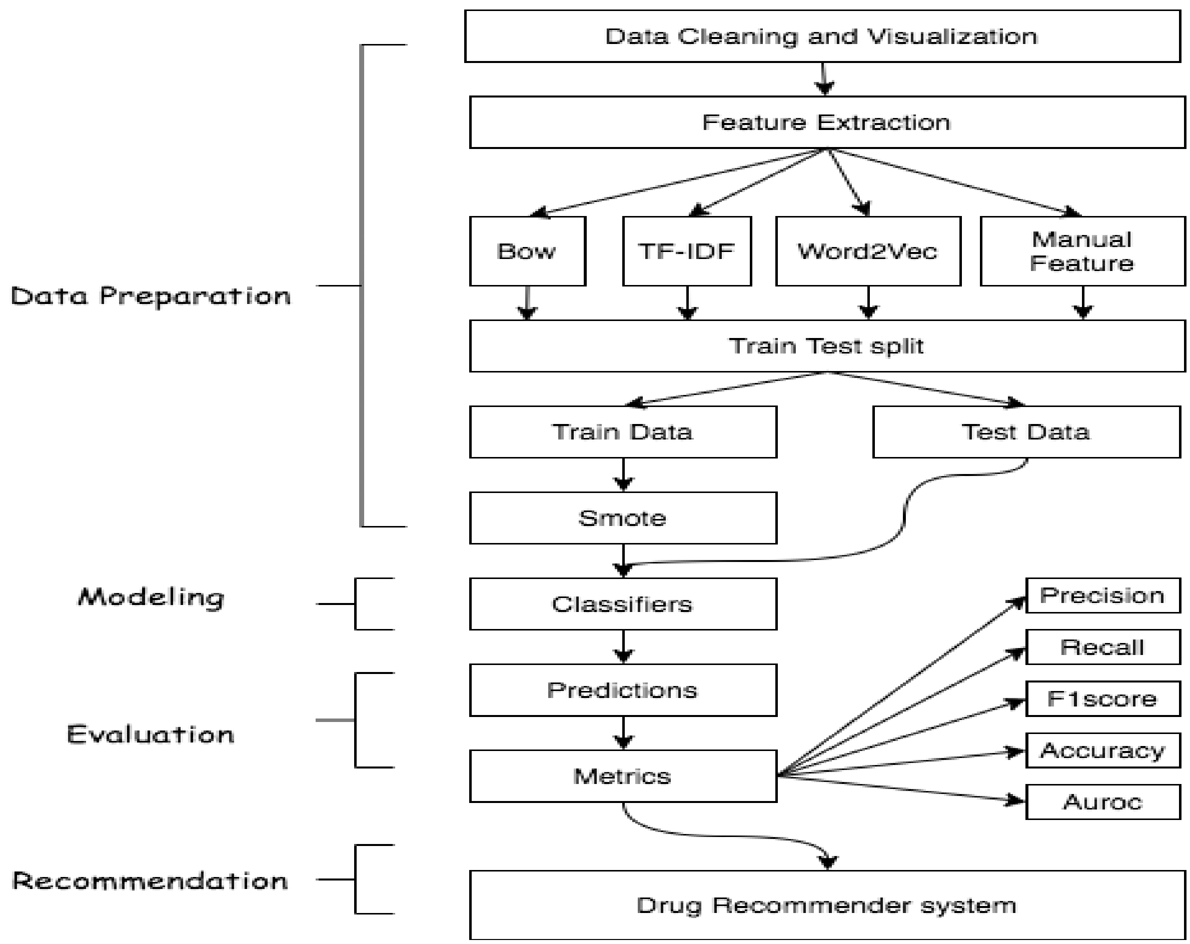

Fig. 1. Flowchart of the proposed model

A. Data Cleaning and Visualization

Applied standard Data preparation techniques like checking null values, duplicate rows, removing unnecessary values, and text from rows in this research. Subsequently, removed all 1200 null values rows in the conditions column. We make sure that a unique id should be unique to remove duplicity.

B. Feature Extraction

After text preprocessing, a proper set up of the data required to build classifiers for sentiment analysis. Machine learning algorithms can't work with text straightforwardly; it should be changed over into numerical format. In particular, vectors of numbers. A well-known and straightforward strategy for feature extraction with text information used in this research is the bag of words (Bow) [16], TF-IDF [17], Word2Vec [18]. Also used some feature engineering techniques to extract features manually from the review column to create another model called manual feature aside from Bow, TF-IDF, and Word2Vec.

Word2Vec: Even though TF and TF-IDF are famous vec- torization methods used in different natural language preparing tasks [27], they disregard the semantic and syntactic like- nesses between words. For instance, in both TF and TF-IDF extraction methods, the words lovely and delightful are called two unique words in both TF and TF-IDF vectorization techniques although they are almost equivalents. Word2Vec

[18] is a model used to produce word embedding. Word- embeddings reproduced from gigantic corpora utilizing various deep learning models [19]. Word2Vec takes an enormous corpus of text as an input and outputs a vector space, generally composed of hundred dimensions. The fundamental thought was to take the semantic meaning of words and arrange vectors of words in vector space with the ultimate objective that words that share similar sense in the dataset are found close to one another in vectors space.

Manual Features: Feature engineering is a popular concept which helps to increase the accuracy of the model. We used fifteen features, which include useful count, the condition column which is label encoded using label encoder function from Scikit library, day, month, year features were developed from date column using Date Time function using pandas. Textblob toolkit [20] was used to extract the cleaned and uncleaned reviews polarity and added as features along with a total of 8 features generated from each of the text reviews .

C. Train Test Split

We created four datasets using Bow, TF-IDF, Word2Vec, and manual features. These four datasets were split into 75% of training and 25% of testing. While splitting the data, we set an equal random state to ensure the same set of random numbers generated for the train test split of all four generated datasets. a synthetic minority over-sampling technique (Smote) [22] to prevent the class imbalance problem. Smote is an over-sampling technique that synthesized new data from existing data. Smote generates the new minority class data by linear interpolation of randomly selected minority instance ’a’ in combination with its k nearest neighbor instance ’b’ in the feature space. Table II shows the total distribution of data on final dataset i.e. after data cleaning. Fig. 6 shows the projection of non-smote and smote using t-distributed stochastic neighbor embedding (t-SNE) [21] of 1000 rows on manual features data. It displays that there are more orange points in the non-smote t-SNE projection, which represents the majority class domi- nance. It also shows that there has been an increment in blue points after using smote that brings out the balance between a majority and minority class that curbs the predominance of the majority class.

E. Classifiers

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, Ran- domForest, 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 al- gorithms only that reduces the training time and give faster predictions.

F. Metrics

The predicted sentiment were measured using five metrics, namely, precision (Prec), recall (Rec), f1score (F1), accuracy (Acc.) and AUC score [23]. Let the letter be: Tp = True positive or occurrences where model predicted the positive sentiment truly, Tn = True negative or occurrences where model predicted the negative class truly, Fp = False positive or occurrences where model predicted the positive class falsely, Fn = False negative or occurrences where model predicted the negative class falsely, Precision, recall, accuracy, and f1score shown in equations given below, TP while building the recommender system, we normalized useful count by conditions.

IV. 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, ap- plied 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 over- sampling techniques, using different values of n-grams, and optimization of algorithms to improve the performance of the recommender system.

V. REFERENCES

[1] Telemedicine, https://www.mohfw.gov.in/pdf/Telemedicine.pdf

[2] Wittich CM, Burkle CM, Lanier WL. Medication errors: an overview for clinicians. Mayo Clin Proc. 2014 Aug;89(8):1116-25.

[3] CHEN, M. R., & WANG, H. F. (2013). The reason and prevention of hospital medication errors. Practical Journal of Clinical Medicine, 4.

[4] Drug Review Dataset, https://archive.ics.uci.edu/ml/datasets/Drug%2BReview%2BDataset%2B%2528Drugs.com%2 529#

[5] Fox, Susannah, and Maeve Duggan. ”Health online 2013. 2013.” URL: http://pewinternet.org/Reports/2013/Health- online.aspx

[6] Bartlett JG, Dowell SF, Mandell LA, File TM Jr, Musher DM, Fine MJ. Practice guidelines for the management of community-acquired pneumonia in adults. Infectious Diseases Society of America. Clin Infect Dis. 2000 Aug;31(2):347-82. doi: 10.1086/313954. Epub 2000 Sep 7. PMID: 10987697; PMCID: PMC7109923.

[7] Fox, Susannah & Duggan, Maeve. (2012). Health Online 2013. Pew Research Internet Project Report.

[8] T. N. Tekade and M. Emmanuel, ”Probabilistic aspect mining approach for interpretation and evaluation of drug reviews,” 2016 International Conference on Signal Processing, Communication, Power and Embed- ded System (SCOPES), Paralakhemundi, 2016, pp. 1471-1476, doi: 10.1109/SCOPES.2016.7955684.

[9] Doulaverakis, C., Nikolaidis, G., Kleontas, A. et al. GalenOWL: Ontology-based drug recommendations discovery. J Biomed Semant 3, 14 (2012). https://doi.org/10.1186/2041-1480-3-14

[10] Leilei Sun, Chuanren Liu, Chonghui Guo, Hui Xiong, and Yanming Xie. 2016. Data-driven Automatic Treatment Regimen Development and Recommendation. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD ’16). Association for Computing Machinery, New

York, NY, USA, 1865–1874. DOI:https://doi.org/10.1145/2939672.2939866

[11] V. Goel, A. K. Gupta and N. Kumar, ”Sentiment Analysis of Mul- tilingual Twitter Data using Natural Language Processing,” 2018 8th International Conference on Communication Systems and Net- work Technologies (CSNT), Bhopal, India, 2018, pp. 208-212, doi: 10.1109/CSNT.2018.8820254.

[12] Shimada K, Takada H, Mitsuyama S, et al. Drug-recommendation system for patients with infectious diseases. AMIA Annu Symp Proc. 2005;2005:1112.

[13] Y. Bao and X. Jiang, ”An intelligent medicine recommender sys- tem framework,” 2016 IEEE 11th Conference on Industrial Elec- tronics and Applications (ICIEA), Hefei, 2016, pp. 1383-1388, doi: 10.1109/ICIEA.2016.7603801.

[14] 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.

[15] 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. 1570-1577, doi: 10.1109/IJCNN.2016.7727385.

[16] Zhang, Yin & Jin, Rong & Zhou, Zhi-Hua. (2010). Understanding bag-of-words model: A statistical framework. International Journal of Machine Learning and Cybernetics. 1. 43-52. 10.1007/s13042-010-0001- 0.

[17] J. Ramos et al., “Using tf-idf to determine word relevance in docu- ment queries,” in Proceedings of the first instructional conference on machinelearning, vol. 242, pp. 133–142, Piscataway, NJ, 2003.

[18] Yoav Goldberg and Omer Levy. word2vec Explained: deriving Mikolov et al.’s negative-sampling word-embedding method, 2014; arXiv:1402.3722.

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

[20] Textblob, https://textblob.readthedocs.io/en/dev/.

[21] van der Maaten, Laurens & Hinton, Geoffrey. (2008). Viualizing data using t-SNE. Journal of Machine Learning Research. 9. 2579- 2605.

[22] N. V. Chawla, K. W. Bowyer, L. O. Hall and W. P. Kegelmeyer. SMOTE: Synthetic

Author's Profile:

Ms.V.R. SWETHA currently working as Assistant Professor in Audisankara college of Engineering & Technology AUTONOMOUS Gudur, Tirupati (Dt), Andhra Pradesh, India.

Ms. P. RAJANI is pursuing MCA from Audisankara College of Engineering & Technology, AUTONOMOUS, Gudur. Affiliated to JNTUA, Andhra Pradesh, India.