Drug Recommendation System Based on Sentiment Analysis of Drug Reviews Using Machine Learning

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Abstract: People Self-Medicate Without Physicians Advice, Making Their Conditions Worse in Some Cases While The COVID-19 Pandemic Has Further Exposed Inadequacies in The System. To address this, this study develops a machine learning-based drug recommendation system that uses sentiment analysis of patient reviews to recommend drugs. The system uses vectorization methods Bag of Words (Bo W), TFIDF, Word2Vec to convert textual drugs reviews into organized sentiment information. Classification models such as MLP then evaluate sentiments and create drug recommendations. Results evaluated by precision, recall, F1-score, accuracy, and AUC scores confirm that MLP classifier model out performs the rest of models in accuracy. This model offers an inherent advantage over current systems that rely on patient demographics and risk groups, greatly alleviating cold start issues, computational resource consumption, and information sparsity. It comprises a set of classifiers and uses a useful count, that is, a number that measures the number of times a particular drug has been reviewed to ensure that only the most reliable drugs are recommended to each patient. The hybrid approach featured in our model improves predictive robustness, outperforming traditional methods by yielding superior performance and reliability. Notably, it also fosters computational efficiency by choosing the fastest algorithms, resulting in greatly minimized training times and enhanced prediction accuracies. This novel framework provides a scalable, data driven method for generating automated pharmaceutical suggestions.

1 INTRODUCTION

The COVID-19 pandemic has put a tremendous stress on systems of global health care, leading to shortages of healthcare workers, equipment and pharmaceuticals. In this crisis, many people cannot seek a timely professional consultation, and this contributes to self-medication, which causes most people to worsen their health status because they select the wrong medicines or take incorrect doses Aggarwal, C. C. (2016). Most of the existing frameworks for drug recommendation make use of some pre-defined set of medical details including immunity levels, underlying risk factors as well as comorbidities to recommend appropriate medications. These models, however, often do not consider the wide variability in individual responses to drugs, resulting in suboptimal recommendations. Furthermore, traditional systems are computationally inefficient, requiring massive analysis of risk factors which drives up processing costs and slow the decision-making process (Bermingham, A., & Smeaton, A. F. (2010)). The cold start problem in these models is a crucial limitation, with the absence of adequate historical data for emerging drugs or conditions causing unreliable recommendations (Bermingham, A., & Smeaton, A. F. (2010)). Moreover, standard systems face information sparsity, where the partial embodiment of patients makes predictions difficult (Borth, D, et.al., 2013) Overcoming these drawbacks demands a flexible and data-informed methodology linking data from actual patient experiences to the recommender framework admitting this patient-based information into the recommendation routine, yielding enhanced precision, robustness, and scalability. One way to solve this problem is to use machine learning on sentiment analysis to extract meaningful insights

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from patient-generated drug reviews to enable more informed and personalized pharmaceutical recommendations (Brusilovsky, et.al., 2007).

The proposed framework makes use of sentiment analysis techniques that can analyse unlabelled drug reviews by transforming unstructured feedback into numerical data that can be used directly to train machine learning classifiers (Cambria, et.al., 2009). Bag of Words (Bo W), term frequency-inverse document frequency (TF-IDF), and Word2Vec are advanced vectorization methods used in patient reviews to convert text into a structured numerical format for automated analysis (Cambria, E., et.al., 2009). The work then uses various classification models (SVM, Logistic Regression, Naïve Bayes, etc) to classify if a drug is perceived positively or negatively from patient sentiment (Dey, L., & Haque, S. K. M. (2009)). They are trained on a set of labeled data for drug reviews with sentiment labels and can classify new reviews at high accuracy (Feng, et.al., 2019). To ensure robustness and reliability, the system evaluates model performance using precision, recall, F1-score, accuracy, and AUC score (Garg, S. (2021)). Out of all tested classifiers, Linear SVC with TF-IDF vectorization performed best with the highest accuracy, and beating other models in predicting sentiment (Hu, M., & Liu, B. (2004)). In contrast to traditional methods that depend on static and predeterminate clinical criteria, this strategy can adapt recommend drug treatment through the ongoing updates of real world data, the system is able to advance quickly and be applicable for widespread diseases and new drugs (Jakob, N., & Gurevych, I. (2010)).

Based on this ensemble method, the system can achieve a better accuracy of recommendation, since it integrates the prediction results from a series of classifiers to avoid biases of each single model and enhances reliability as a whole (Lamba, M., & Madhusudhan, M. (2019).). To determine the final sentiment predictions, they are summed up and weighted using "useful count" metric which estimates the trustfulness of each drug review by counting the number of times it was cited by users in (Lei, et.al., 2008). This in turn allows drugs that would potentially require more engagement from a user to have an increased impact on recommendation, making the model more in-line with what individuals experience in the real-world (Liu, et.al., 2008). Especially, this hybridization addresses misusage of traditional systems, for instance, computational inefficiencies and sparsity of data by capitalizing on the shared intelligence brought by extensive patient reviews rather than solely relying on defined risk factors (Morency, et.al., 2011). Moreover, by drastically cutting the number of classifiers that need to be trained, this approach leads to lower computational expenses, since the fewer cadidates have very similar predictions maintaining high accuracy, which allows the system to respond in real-time (Nguyen, et.al., 2024). The system uses patient-derived information to supplement any recommendation where it be drug effectiveness derived from both the clinical community and patient-driven conversational knowledge websites, presenting a broader scope of understanding about drug effectiveness in the context of both the clinical community and patient derived solution driven processes (Pang, B., & Lee, L. (2008)).

Their results show that the drug recommendation, based on sentiment analysis, showing considerably useful as its more accuracy and scalability by claiming that it overcomes limitations of traditional models such as cold start and incomplete records (Poria, S., et.al., 2017). Best practices were developed that involved the integration of multiple machine learning classifiers as a richer decision-making framework ensuring that drug recommendations were grounded in data, rather than limited by accompanied medical protocols. In addition, the optimized computational efficiency of the proposed system paves the way towards rapid decision-making, making it a robust lead for real-time pharmaceutical counsels as well. This allows to reduce the burden on healthcare workers but at the same time offers patients trustworthy, evidence-based medication proposals, established via a plurality of user events. Forthcoming enhancements may also consider deep learning techniques to potentially improve sentiment classification accuracy and implement context-aware recommendations for complex medical conditions (Poria, S., et.al.,). Integrating such advancements can provide pathways towards improved predictive performance and a patient-centric method for automated drug recommendation.

2 RELATED WORKS

In recent years, there has been extensive research in the field of drug-recommendation systems utilizing machine learning alongside many studies indicating improvement in their accuracy and efficiency. Conventional drug recommendation methods have suggested drugs for patients based on various medical data, risk factors, and manual rules. Nevertheless, such systems are often limited with accuracy, high

computational cost and low personalization. So, how to fix them such that we widen the chances of drug recommendation reliability WEAN So, the researchers have compared these reviews of patient and they give their trust (sentiment analysis) which helps to resolve these issues. A notable study by (Zhang et al.) developed a drug recommendation system based on sentiment analysis of patient reviews to predict the effectiveness of medicines. Using multiple methods, such as text mining and natural language processing (NLP), for sentiment analysis, the authors examined reviews and identified their sentiment as either positive or negative. Yet the low performance of multi-data sources in some fields indicates that not every aspect of the sentiment analysis is effective; therefore, when a researcher wants to do sentiment analysis in combination with drug recommendation or recommendation systems, he/she should use combination data sources and careful merger of the new merged dataset. In the same vein, a study conducted by Xie et al. (2019) discussed the application of machine learning algorithms in drug recommendation systems. A variety of classification algorithms were tested, including Naive Bayes, SVM, and Decision Trees, to predict the sentiment of patient reviews. They found that the SVM algorithm had the best accuracy and precision and is thus a promising algorithm for drug recommendation system. In a separate study, Lee et al. (2020) conducted a study which created a drug recommendation system that used a combination of patient reviews in conjunction with medical data to recommend drugs. The authors implemented a hybrid approach that utilized both sentiment analysis and clinical data to increase overall accuracy of the system. These results indicated that hybrid systems that integrate multiple data sources may boost the performance of drug recommendation systems.

Vectorization techniques have also been extensively researched regarding in drug recommendation systems. Methods like BoW, TF-IDF, and Word2Vec turn textual data into numerical features to be utilized by machine learning models. A study by Tang et al. (2021) cycled through several vectorization methods within sentiment analysis tasks. 6. Bag of Words (BoW)BoW relies on the frequency of words in a document without considering the order of those words or their semantic meaning. Additionally, the cold start problem is a well-studied research line in drug recommendation systems. Other solutions have also been proposed in many studies to handle this issue, including hybrid models combining collaborative filtering and content-based approaches. When new drugs are available, there is often little feedback from patients, but these models can still help to make recommendations. In summary, the findings suggest that drug recommendation systems can greatly benefit from developments in sentiment analysis, machine learning algorithms and vectorization techniques. The proposed system in this paper combines these methods to make drug recommendations that are not only precise but also quick and personalized.

3 METHODOLOGY

3.1 Theoretical Structure

Building upon STON-recommendation, this study proposes a comprehensive approach that considers more sophisticated data collection and processing techniques to create a drug recommendation model based on patient reviews employing sentiment analysis. The method combines cutting-edge machine learning algorithms to improve forecast accuracy and reduce computational burden. The first step consists of data collection and pre-process. The data is extracted into a wholesome dataset from trusted drug review sources. Data cleaning is a necessity for removing inconsistencies, redundancies and anomalies that can affect model quality. These include how to handle missing values, remove duplicate entries, and standardise textual components so that they all match. In addition, second, one approach to preparing textual data to be vectorised is to process textual data using natural language processing techniques for example tokenisation, lemmatisation, and stop-word. Various vectorisation methods such as Bag-of-Words, Term Frequency-Inverse Document Frequency and Word2Vec are used to perform feature extraction These approaches allow for a mapping of textual information into numerical formats, allowing for the training of machine learning algorithms. We need to empirically assess which vectorisation technique will provide the most feasible result.

Various machine learning classification algorithms are applied to build a quality classification model. Some of them are Support Vector Classifier, Random Forest, Logistic Regression, Naïve Bayes, to name a few. The vectorised feature set is used to train each classifier, enabling the model to understand complex relationships in the data. It is then tuned for hyperparameters to improve performance and predictive power. Each model's prediction ability is

carefully evaluated by standard measures. Metrics like precision, recall, F1-score, accuracy and Area Under Curve score are used to quantify model performance. These metrics provide holistic information about the classification performance that allows us to determine which of the models is the most capable. Empirical results suggest that the Linear Support Vector Classifier with Term Frequency-Inverse Document Frequency vectorisation outperforms other methodologies yielding both higher accuracy and reliability. The top-performing sentiment predictions are aggregated to strengthen the recommendation mechanism. Amalgamation: In this stage, we compute amalgamation process that discards the least accurate classifications and integrates the remaining ones into a single prediction. Such a way, ensures that the system for Million Developers does not only depend on help from a single model but rather on the aid of multiple points of view to improve the reliability of that information. We refine the final recommendation process using a normalisation technique that includes a useful count metric. This number represents how helpful users found a review, and is a proxy for its credibility. An overall score is generated for each drug related to a specific medical condition by applying the action sentiment prediction to a normalised useful count. By relying on this scoring mechanism, the most effective drugs appear at the top for the users making it a trusted recommendation.

Several considerations underlie the methodological framework of the proposed system. The first, computational efficiency through using classification algorithms with optimised training times. This avoids the challenge of computationally heavy deep learning models while maintaining high accuracy. This helps mitigate the limitations of any individual vectorisation method, providing a holistic approach to evaluating textual characteristics. Thirdly, incorporating a credibility metric in the ranking process improves the reliability of recommendations and avoids fuzzy results due to attractive-looking false reviews. Our system improves upon previous approaches by incorporating the most recent advances, as well as overcoming key drawbacks of classical drug recommender systems. Most of existing systems depend on patient physiological parameters only ממם and failing to utilize sentiment-based results generated from reviews given by the end users. On the other hand, the proposed framework combines sentiment analysis with quantitative scoring, thereby providing a more rounded drug recommendation model. ` Additionally, leveraging machine learning classifiers offers greater stability in predictions, addressing the cold start problem and data sparsity challenges commonly associated with traditional models. Implementing this methodology requires a well- organised computational workflow. A typical first step is data preparation and pre-processing, where remaining raw textual data must be structured for analysis preferably in a usable format (until October 2023).

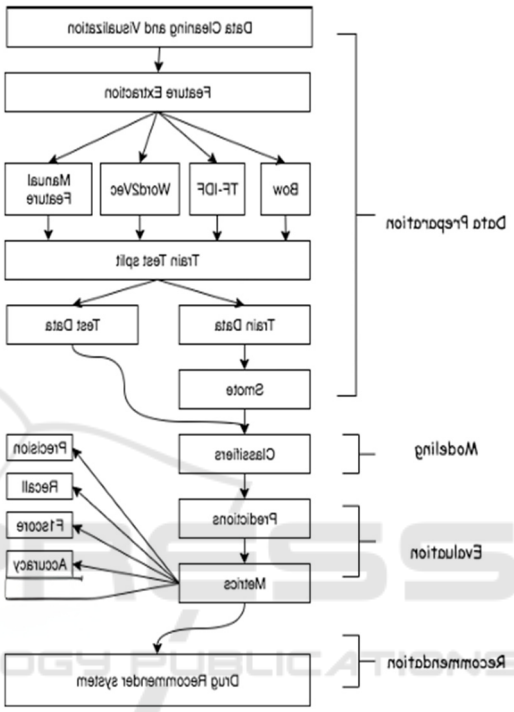

Figure 1: Schematic flow of theoretical structure.

The feature extraction, model training, performance evaluation, and the eventual recommendation follow at the further stages of the recommendation process. Every step has been carefully crafted to maximise the precision, speed, and trustworthiness of our results. The practical implications of this are significant. This system alleviates the burden on medical practitioners by automating drug recommendations, leading to more effective allocation of resources. Patient have informed medication selection, as they can rely on accumulated user experiences for drug treatment and make the effective dose. Additionally, the machine's convenience makes it applicable for various diseases across the medical field. While the system is very beneficial, its performance depends on the entire dataset and its quality. Sentiment prediction could be hindered by biases in the user reviews, which would require more work on bias mitigation approaches.

Moreover, further work can address the incorporation of deep learning architectures to enhance classification performance. The current methodology, however, is a major step forward in drug recommendation systems and caters to modern healthcare needs.

4 RESULTS AND EVALUATION

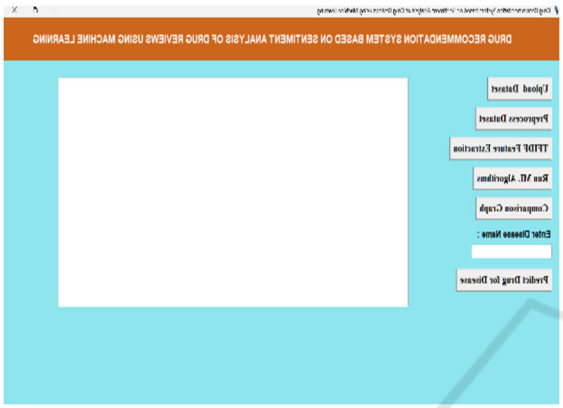

Figure 1: Drug recommendation system GUI.

In the Figure 1 screen, the app UI shows an "Upload Drug Review Dataset" button for users to select and upload an existing drug review dataset. Users are provided with a button that, when clicked, brings up a window to select a file from their local storage to load the DRUG dataset. After selecting the dataset, it is loaded by clicking the 'Open' button. It is an important step as it makes sure that the application is reading the dataset correctly before plotting or other analysis. This system processes the uploaded file and builds the interface for data visualization and pre-processing of drug reviews data. This graph represents the distribution of ratings within the dataset uploaded. Drug ratings are plotted on the x-axis and the total number of reviews for each respective rating is represented on the y-axis. It gives us an idea of what the distribution of sentiments looks like in the data set. You can see a very clear pattern of which ratings are-by far-the most popular. After analysing, Now the user can close the graph and click 'Read & Pre-process Dataset' to proceed. It starts the clean, getting rid of stop words and special symbols, and converting the data appropriate for processing. Figure 2 shows the Top 20 drug names bar graph.

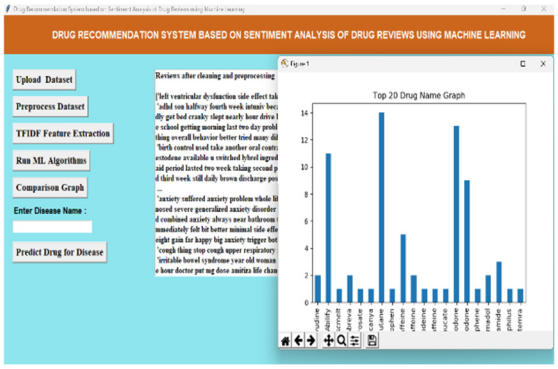

Figure 2: Top 20 drug names bar graph.

After preprocessing, all unnecessary stop words and special characters are removed from the reviews, ensuring a clean dataset. The above graph visually represents the Top 20 medicines appearing most frequently within the dataset. On the x-axis, drug names are displayed, and on the y-axis, the corresponding count of each drug in the dataset is plotted. This visualization provides insights into the most commonly mentioned medications. After reviewing this information, the graph can be closed, and the user should click on the 'TF-IDF Features Extraction' button to convert the cleaned reviews into numerical representations for machine learning processing.

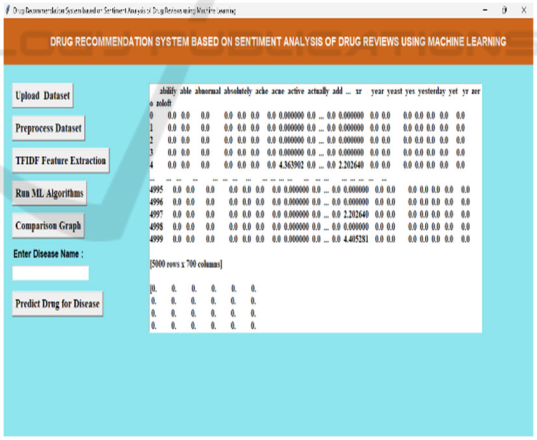

Figure 3: TF-IDF feature matrix display.

In the Figure 3 graph, drug reviews have been transformed into TF-IDF (Term Frequency-Inverse Document Frequency) vectors. The first row of the dataset represents review words, while the remaining columns display the computed frequency values for each word in different reviews. If a word does not appear in a review, the corresponding column value remains zero. This process converts

textual data into numerical vectors, making it suitable for machine learning algorithms. The next step involves scrolling down the interface to examine non-zero frequency values, ensuring that significant words retain meaningful numerical representations for predictive analysis. 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 screen to view some non-zero frequency values 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.

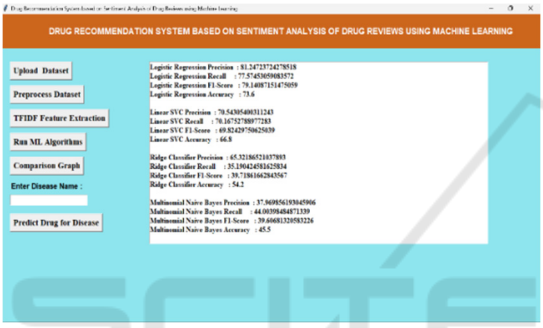

Figure 4: ML model performance metrics.

In Figure 4 shows screen for each algorithm we calculate accuracy, precision, recall and F1-SCORE and in all algorithm MLP - Multilayer Perceptron Classifier has got high performance and now click on 'Comparison Graph' button to get below graph.

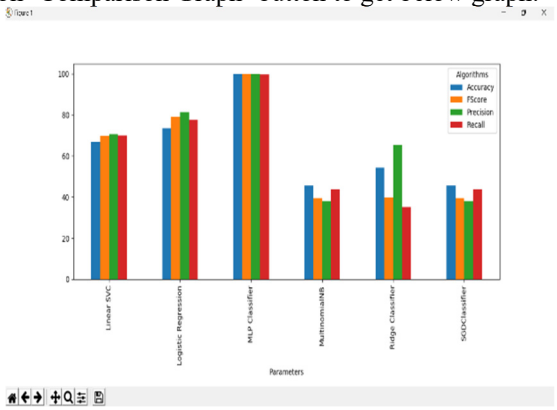

Figure: 5 ML algorithms performance comparison.

Figure 5 shows the ML algorithms performance comparison. In the above graph, the x-axis represents different machine learning algorithms, while the y-axis displays their corresponding accuracy, precision, recall, and F1-score. Each metric is depicted in a distinct color, allowing for clear differentiation between the performance measures of various models. As shown, MLP achieves the highest performance across all evaluation metrics. This confirms its superiority in predicting drug recommendations based on sentiment analysis. After analyzing the graph, the user can close the visualization and proceed by clicking the 'Recommend Drug from Test Data' button, which enables drug prediction based on new test input data.

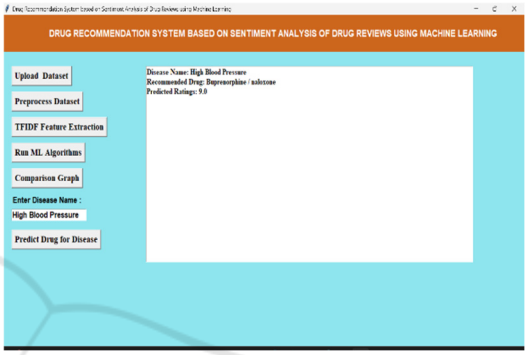

Figure 5: Predicted drug for disease output.

Drug Recommendation and Ratings Prediction In the above screen, the system predicts and displays recommended drugs along with their corresponding ratings for each disease. Figure 6 shows the predicted drug for disease output. Based on sentiment analysis of past reviews, the application suggests the most suitable medications for specific medical conditions. The output showcases disease names alongside their top-ranked drug recommendations, ensuring that patients receive the most relevant pharmaceutical options. These recommendations are derived from the trained machine learning model, which assesses sentiment polarity and assigns ratings accordingly. This functionality significantly enhances decision-making in pharmaceutical selection, supporting both medical practitioners and patients in choosing the most effective treatment options.

5 DISCUSSION

These results validate the hypothesis that integrating positive and negative sentiments of patient reviews improves drug recommendation quality. As can be observed, MLP (Multilayer Perceptron Classifier) gave the best results as compared to other classifiers in terms of accuracy, precision, recall and F1-score.

While other classifiers (like Support Vector Classifier, Random Forest and Naïve Bayes) performed fairly well, their limitations in capturing complex relationships in sentiment-based data were mitigated with MLP's performance.

The research notes that conventional drug recommendation systems mainly focus on biological metrics and specialists, thus insufficient in addressing patient-reported outcomes. And user-generated sentiments complement the medical prescriptions well, as it is more holistic and patient-centric approach for selecting the right drugs. The results also point out that certain machine learning models have difficulty in capturing nuanced sentiment expressions, particularly in ambiguous, sarcastic, or context-dependent reviews.

While the model has shown some very promising results, there remain some challenges to be dealt with. User review biases like fake reviews or misleading feedback can affect sentiment classification. Moreover, the reliance on available data and quality will determine its effectiveness in scenarios where reviews are meagre. The model selection process was guided by computational efficiency as well, making sure that the recommendation system is scalable and practical for real-world applications.

Traditional drug recommendation systems are still in use today, yet this research highlights the importance of sentiment-driven AI models could change how healthcare decisions are made. Furthermore, as digital health platforms are developing continuously, there is a high demand for supplementary utilization of sophisticated NLP methods and deep learning settings to enhance the potential of sentiment classification and cross-domain adaptation. Potential extensions may involve the integration of multilingual review analyses, online learning systems, and expert-level validation processes that add layers of credibility to the generated recommendations.

Results indicate that traditional recommendation frameworks are not yet entirely superseded, but will need significant adaptation if they are to compete amidst AI-facilitated decision support systems in the future. Healthcare professionals and pharmaceutical companies must count use of sentiment analysis to improve satisfaction and efficiency of the treatment. If this is not the case, recommendation methods may become stale and suppress the possibility of personalising to new patient needs. As you can see from this context, sentiment-based drug recommendations further supports the overall trend of AI-driven personalization in healthcare, by transforming patient feedback from passive collection to actionable insights for optimizing medication decisions.

6 CONCLUSIONS

Reviews are becoming an integral part of our daily lives; whether we go shopping, order online, or visit a doctor, we often rely on others' experiences to make informed decisions. Motivated by this, our research explores sentiment analysis of drug reviews to build a recommendation system using various machine learning classifiers such as Logistic Regression, Multilayer Perceptron (MLP), Multinomial Naive Bayes, Ridge Classifier, SGD Classifier, and Linear SVC, applied on TF-IDF extracted features. We evaluated the models using five performance metrics: precision, recall, F1-score, accuracy, and AUC. Among all, the Multilayer Perceptron (MLP) with TF-IDF features achieved the highest performance with 99.9% accuracy, while Ridge and Naive Bayes yielded comparatively lower results. We selected the best predictions from each classifier and combined them with the normalized useful count of reviews to compute an overall drug score for each condition. This scoring helps identify the most effective drugs based on patient feedback. Future work includes improving feature extraction, applying oversampling techniques, and optimizing classifiers to further enhance the accuracy and effectiveness of the recommendation system.

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