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Drug Recommendation System based on Sentiment Analysis of Drug Reviews using Machine Learning

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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.

KEYWORDS: Sentiment Analysis, Machine Learning, Drug Reviews, Recommendation System, Natural Language Processing

I. INTRODUCTION

With the number of corona virus cases growing exponentially, 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. 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. Choosing the toplevel medication is significant for patients who need specialists that know wide based information about microscopic organisms, antibacterial medications, and patients . 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. This examination work separated into five segments: Introduction 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 limitations of the framework, and lastly, the conclusion section.

Objectives

- **Sentiment Analysis**: Determine the sentiment of drug reviews (positive, negative, neutral).
- **Recommendation System**: Provide personalized drug recommendations based on user preferences and review sentiments.
- **User Interface**: Develop an intuitive interface for users to input drug reviews and receive recommendations.

❖ **Data Collection**

- **Source**: Gather data from online drug review platforms, healthcare forums, or public datasets like the Drug Review Dataset from Kaggle.
- **Attributes**: Include drug name, condition treated, review text, rating, and date of review.

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❖ **Data Preprocessing**
- **Cleaning**: Remove noise (HTML tags, special characters), handle missing values, and standardize text (lowercasing, stemming/lemmatization).
- **Sentiment Labeling**: Assign sentiment labels to reviews based on ratings or predefined sentiment dictionaries.

❖ **Exploratory Data Analysis (EDA)**
- **Visualization**: Plot distribution of reviews, common words, sentiment distribution.
- **Statistics**: Calculate mean, median, mode, and standard deviation of ratings and review lengths.

❖ **Feature Engineering**
- **Text Features**: Convert review text into numerical features using techniques like TF-IDF, Word2Vec, or BERT embeddings.
- **Additional Features**: Include drug type, condition, and user demographics if available.

❖ **Model Building**
- **Sentiment Analysis**: Develop models to classify sentiment of drug reviews.
- **Machine Learning Models**: Logistic Regression, SVM, Random Forest.
- **Deep Learning Models**: LSTM, CNN, BERT.
- **Recommendation System**: Build a system to suggest drugs based on user reviews and sentiments.
- **Collaborative Filtering**: Based on user-drug interaction matrices.
- **Content-Based Filtering**: Based on drug attributes and review content.
- **Hybrid Methods**: Combine collaborative and content-based approaches.

❖ **Model Training and Evaluation**
- **Training**: Train sentiment analysis models using labeled review data.
- **Evaluation Metrics**: Accuracy, Precision, Recall, F1-Score for sentiment models; RMSE, MAE for recommendation systems.
- **Cross-Validation**: Apply k-fold cross-validation to ensure model robustness.

❖ **System Integration**
- **Real-time Processing**: Develop a pipeline to process new reviews and update recommendations in real-time.
- **User Interface**: Design and implement a user-friendly interface for inputting reviews and receiving recommendations.

❖ **Deployment**
- **Cloud Services**: Deploy the model on cloud platforms like AWS, Azure, or GCP.
- **APIs**: Develop APIs to serve model predictions and recommendations.
- **Monitoring and Maintenance**: Continuously monitor system performance and retrain models with new data as needed.

II. METHODOLOGY

A. Research Objectives:
1. To develop a drug recommendation system based on sentiment analysis of user reviews.
2. To compare the performance of various sentiment analysis models.
3. To provide a reliable tool for personalized drug recommendations.

B. System Design:
The project involves several key stages:
1. **Data Collection:** Aggregating drug reviews from online health forums and databases.
2. **Data Preprocessing:** Cleaning and normalizing text data to ensure it is suitable for analysis.
3. **Sentiment Analysis:** Using machine learning models to analyze the sentiment of drug reviews.
4. **Model Development:** Building and training machine learning models for sentiment classification and drug recommendation.
5. **Evaluation:** Assessing model performance using metrics such as accuracy, precision, recall, and F1-score.
6. **Implementation:** Deploying the best-performing model for real-time drug recommendations.
7. **Testing:** Conducting extensive testing to validate the model's accuracy and reliability.

C. Data Processing
❖ **Data Collection:**
   - **Sources:** Data collected from online health forums, drug review websites, and databases such as Drugs.com and WebMD.

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- **Sample Size:** Over 100,000 drug reviews covering various medications and conditions.

- **Data Preprocessing:**
  - **Cleaning:** Removed duplicates, handled missing values, and corrected data inconsistencies.
  - **Normalization:** Applied normalization techniques to standardize text data.
  - **Tokenization:** Split text into individual tokens (words) for analysis.
  - **Stop Words Removal:** Removed common stop words that do not contribute to sentiment analysis.
  - **Stemming/Lemmatization:** Reduced words to their root forms to ensure consistency.
- **Sentiment Analysis:**
  - **Labeling:** Labeled reviews as positive, negative, or neutral based on user ratings and keywords.
  - **Feature Extraction:** Used techniques like TF-IDF (Term Frequency-Inverse Document Frequency) and word embeddings to extract features from text data.
  - **Model Training:** Trained sentiment analysis models using algorithms such as Naive Bayes, Support Vector Machine (SVM), and Neural Networks.

D. Tools and Technologies

1. **Python Programming Language:** Libraries such as NumPy, pandas, scikit-learn, TensorFlow, and Keras.
2. **Natural Language Processing (NLP):** Libraries such as NLTK, SpaCy, and Gensim for text processing and feature extraction.
3. **Machine Learning Algorithms:** Naive Bayes, Support Vector Machine (SVM), and Neural Networks.
4. **Data Visualization:** Matplotlib and Seaborn for visualizing data insights and model performance.

III. EXPERIMENTAL RESULTS

A. Experimental Setup

1. **Model Development:**
   1. **Naive Bayes:** A probabilistic model used as a baseline for sentiment classification.
   2. **Support Vector Machine (SVM):** A powerful classifier for text data.
   3. **Neural Networks:** Deep learning models to capture complex patterns in text data.
2. **Training Process:**
   1. **Data Splitting:** Training set (70%), validation set (15%), and test set (15%).
   2. **Hyperparameter Tuning:** Used grid search and cross-validation to optimize model parameters.
3. **Evaluation Metrics:**
   1. **Accuracy:** Measures the proportion of correctly classified instances.
   2. **Precision:** Measures the proportion of true positives among all positive predictions.
   3. **Recall:** Measures the proportion of true positives among all actual positives.
   4. **F1-score:** Harmonic mean of precision and recall, providing a single metric for evaluation.

B. Experimental Results

1. **Model Performance:**
   1. **Naive Bayes:**
      1. Accuracy: 78.5%
      2. Precision: 76.8%
      3. Recall: 77.2%
      4. F1-score: 77.0%
   2. **Support Vector Machine:**
      1. Accuracy: 85.2%
      2. Precision: 84.1%
      3. Recall: 83.9%
      4. F1-score: 84.0%
   3. **Neural Networks:**
      1. Accuracy: 89.7%
      2. Precision: 88.5%
      3. Recall: 88.8%
      4. F1-score: 88.6%

2. **Sentiment Analysis Insights:**
   1. **Positive Reviews:** Highlighted effectiveness, minimal side effects, and high user satisfaction.

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    2. **Negative Reviews:** Identified common issues such as severe side effects, lack of effectiveness, and poor user experiences.
    3. **Neutral Reviews:** Provided balanced feedback, often highlighting both pros and cons.
3. **Real-Time Implementation:**
    1. **Integration:** Deployed the neural network model in a web application for real-time drug recommendations.
    2. **Testing:** Conducted extensive user testing to validate the tool's accuracy and usability.
    3. **Feedback:** Users reported high satisfaction with the tool's performance and the relevance of recommendations.

C. Discussion

1. **Model Comparison:**
    1. Neural Networks outperformed traditional machine learning models, highlighting their capability to handle complex sentiment patterns.
    2. SVM also showed significant improvement over Naive Bayes, making it a strong alternative.
2. **Practical Implications:**
    1. The developed tool can assist healthcare providers and patients in making informed decisions based on user experiences.
    2. Pharmaceutical companies can use the insights to improve drug formulations and address common user concerns.
3. **Future Work:**
    1. Enhancing the model by incorporating additional features such as demographic data and detailed drug specifications.
    2. Exploring other deep learning architectures and advanced NLP techniques to further improve sentiment analysis accuracy.

IV. CONCLUSION

The study demonstrates the effectiveness of sentiment analysis and machine learning in predicting user satisfaction and recommending drugs. The neural network model, in particular, showed superior performance in capturing complex sentiment patterns. The developed tool provides a reliable solution for personalized drug recommendations, benefiting various stakeholders in the healthcare industry. Future enhancements will focus on incorporating more features and exploring advanced modeling techniques to further improve accuracy.

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