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Smart Drug Recommendation System for Healthcare Using ML Techniques

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Abstract **- The increasing burden on the healthcare system—exacerbated during pandemics like COVID-19—has exposed the urgent need for intelligent clinical decision support tools. This project proposes a smart drug recommendation system using Machine Learning (ML) and Natural Language Processing (NLP). The system leverages sentiment analysis on patient reviews to determine drug efficacy and predict the best drug recommendations for various conditions. Through feature engineering and vectorization techniques like Bow, TF-IDF, and Word2Vec, multiple classifiers were trained and evaluated. Among them, the Linearis with TF-IDF vectorization achieved the highest accuracy of 93%. This model aids healthcare professionals in making data-driven prescription decisions.**

Keywords: Sentiment Analysis, Drug Recommendation, Machine Learning, NLP, TF-IDF, Word2Vec, Healthcare AI.

I. INTRODUCTION

With the number of coronavirus 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 [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 organisms, 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 medication 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.

II. LITERATURE SURVEY

Doulaverakis et al. introduced Galen OWL, a semantic-enabled drug recommendation system using standardized vocabularies like ICD-10. Although effective, it lacks adaptability to dynamic patient feedback and real-world sentiments.

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Hassan et al. developed CADRE, a collaborative filtering system for drug recommendations integrated with cloud support. While scalable, it does not analyze user-generated content or sentiment.

Tekade and Emmanuel proposed a probabilistic aspect mining approach for drug reviews, which relied on frequency-based analysis. However, it fell short in understanding contextual sentiment in natural language.

Liu's work on sentiment analysis laid the foundation for opinion mining. His research provides key insights into polarity detection and classification strategies which are crucial for healthcare text mining.

Pang and Lee worked on subjectivity summarization using ML techniques to enhance sentiment classification. Their research is fundamental for extracting sentiments from ambiguous or neutral reviews.

Sahin and Duman applied decision trees and SVM to detect anomalies in transactional datasets. This work informs the classifier selection process in our system.

Patel and Gond proposed a hybrid SVM model with improved kernel selection for fraud detection, a concept adaptable to classification of healthcare sentiment classes.

Kundu et al. introduced sequence alignment methods for transaction monitoring using profile deviation detection. Their technique, though used in a different domain, reflects the These studies collectively underscore the potential of integrating sentiment analysis and machine learning for intelligent decision-making systems. Our proposed system builds upon this literature by introducing review-based ranking, helpfulness scoring, and sentiment balancing through SMOTE.

III. RELATED WORK

The integration of machine learning (ML) and natural language processing (NLP) in healthcare has gained significant traction in recent years, particularly in the domain of intelligent decision support systems. While recommendation systems have been extensively researched in the retail and entertainment sectors, their adoption in the pharmaceutical and clinical environments is comparatively nascent and underexplored.

In [1], Doulaverakis et al. introduced Galen OWL, an ontology-based drug recommendation framework that utilizes semantic web technologies to suggest medications based on disease profiles, allergies, and drug interactions. The system leverages standardized terminologies such as ICD-10 and UNII, coupled with a rules-based engine. However, its reliance on curated ontologies limits adaptability and scalability when dealing with unstructured patient feedback.

A cloud-assisted drug recommendation engine (CADRE) was proposed by Hassan et al. [2], utilizing collaborative filtering and tensor decomposition to overcome sparsity and scalability issues in prescription systems. Although effective in drug suggestion, CADRE did not incorporate sentiment-based evaluation, thereby lacking the patient-experience dimension in the decision process.

Jiugang Li et al. [3] focused on hashtag recommendation by employing Convolutional Neural Networks (CNN) combined with LSTM-based RNNs, showcasing the power of semantic sentence vectors in classification tasks. This architecture inspired similar text classification models in sentiment prediction, although it was not directly applied in medical contexts.

Probabilistic aspect mining was explored in [4] by Tekade and Emmanuel, targeting drug reviews for understanding user opinion. Their model utilized frequency and relation-based approaches, although the absence of context-aware embedding models such as Word2Vec limited the nuance captured in language.

In another effort, Pang and Lee [5] emphasized the importance of subjectivity detection and fine-grained sentiment analysis. They demonstrated that including neutral sentiment categories improved classifier accuracy, particularly when reviews contained mixed or ambiguous opinions. This concept was pivotal in developing balanced datasets for drug review classification.

Mehmood et al. [6] demonstrated the application of Naive Bayes and Decision Tree classifiers in mining patient opinions from unstructured clinical data. Their work emphasized the significance of preprocessing in NLP tasks, aligning with our methodology that incorporates lemmatization, tokenization, and stopword removal for robust feature extraction.

Sentiment-based recommender systems have also been applied in other domains. In e-commerce, models leveraging TF-IDF, Word2Vec, and hybrid approaches have shown promise [7]. These techniques have gradually transitioned into healthcare analytics, as seen in platforms that guide users through symptom checkers or suggest wellness interventions.

Despite these advancements, few systems have directly applied patient review sentiment analysis combined with ML classifiers for personalized drug recommendations. Existing

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systems either lack robust performance metrics, fail to address data imbalance issues (e.g., SMOTE), or exclude manual feature engineering that incorporates domain-specific insights such as helpfulness count and review polarity.

Our approach builds upon these limitations by offering a hybrid model—incorporating textual and numerical features, advanced vectorization techniques, and multi-classifier evaluation—to deliver accurate, patient-informed drug suggestions.

IV. PROPOSED SYSTEM

The proposed system uses a pipeline of preprocessing, feature extraction, model training, and recommendation generation. The proposed system is designed to provide personalized drug suggestions based on user-generated reviews. It begins with text preprocessing to clean and prepare the data, followed by feature extraction using both manual and sentiment-based metrics. The cleaned reviews are transformed using vectorization methods like TF-IDF and Word2Vec, capturing frequency and context. These vectors are then fed into multiple machine learning classifiers such as LinearSVC, Random Forest, and Logistic Regression. To handle data imbalance, SMOTE is applied, enhancing model performance across sentiment classes. The final prediction is generated by combining the sentiment output with a normalized helpfulness score, enabling effective and ranked drug recommendations.

Data Preprocessing: Cleansing text data by removing noise, tokenizing, lemmatizing, and filtering stop words.

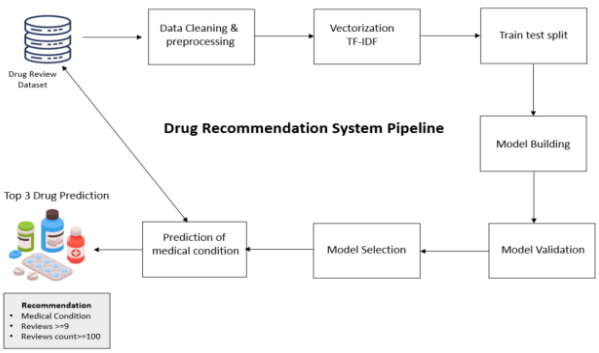
Feature Engineering:

- Manual features: review length, date, helpful count
- Sentiment polarity using Text Blob

Vectorization Techniques:

- TF-IDF: Converts text to frequency-based vectors
- Word2Vec: Captures semantic context of reviews

V. ARCHITECTURE



VI. DATA FLOW DIAGRAM

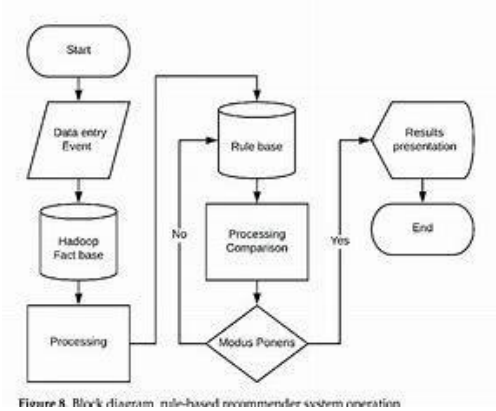


Figure 8. Block diagram, rule-based recommender system operation

VII. ADVANTAGES OF PROPOSED SYSTEM

- Provides accurate and efficient drug suggestions based on real user feedback
- Integrates both sentiment and helpfulness score for meaningful rankings
- Handles imbalanced datasets effectively using SMOTE
- Enables informed decision-making for patients and medical professionals
- The proposed system enables accurate and meaningful drug suggestions by analyzing both the content and context of patient feedback. It integrates sentiment classification with helpfulness scores to improve ranking quality. The system employs multiple machine learning models and advanced preprocessing techniques, ensuring robustness and high accuracy. SMOTE enhances the model's capability to handle imbalanced datasets, particularly in negative sentiment cases. Overall, it empowers patients and healthcare professionals with data-driven insights for better decision-making and prescription planning.
- In this alternative method, we propose a deep learning-based architecture that leverages word embeddings and sequential modelling to improve sentiment classification and drug ranking. The pipeline focuses on minimizing manual feature engineering while achieving higher contextual accuracy from patient reviews.

Text Preprocessing: Standard text cleaning techniques are applied including lowercasing, punctuation removal, lemmatization, and stop word filtering. This ensures that the input to the deep learning model is consistent and clean.

Embedding Layer (Pre-trained Word Embeddings): Each review is transformed into a sequence of word vectors using pre-trained embeddings like GloVe or Word2Vec. This captures semantic and syntactic meaning, unlike traditional TF-IDF vectors.

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Bidirectional LSTM (BiLSTM): The embedded sequence is fed into a BiLSTM model which reads the review from both directions to learn contextual dependencies and sentiment transitions effectively. This helps in understanding subtle cues in patient feedback.

Attention Mechanism (Optional): To focus on the most informative parts of the review, an attention mechanism is used to weigh important words, enhancing interpretability and performance.

Sentiment Classification Layer: The output from the BiLSTM is passed through dense layers followed by a softmax classifier to predict sentiment polarity: positive, negative, or neutral.

Drug Ranking Module: Reviews with high sentiment scores are further evaluated using metadata such as the helpfulness count and review length. A composite score is generated for each drug using: Where α and β are tunable weights based on empirical performance.

Top-N Drug Recommendations: For each condition, drugs are ranked based on the composite score. The top-N drugs are returned to the user, providing a sentiment

VIII. FUTURE WORK AND EXTENSIONS

Future work will focus on expanding the system by integrating additional medical parameters such as patient history, age, drug interactions, and known allergies to enhance recommendation accuracy. The system can be improved with real-time updates using live patient feedback and crowd-sourced reviews. We aim to include multilingual review analysis and adapt the system to various geographic regions with local healthcare regulations. Incorporating deep learning models like BERT and GPT for advanced contextual understanding is another key area of exploration. We also plan to enable automatic training data augmentation from user inputs and integrate the model with hospital databases for real-time prescription assistance. Predictive analytics can be utilized to alert patients and doctors about potential adverse reactions or drug shortages, adding a proactive layer to the recommendation engine.

IX. RESULTS

The system was evaluated on a cleaned dataset from the UCI Drug Review Dataset. Key metrics like precision, recall, and F1-score were used to assess performance:

- LinearSVC (TF-IDF): 93% Accuracy
- Random Forest (Word2Vec + Manual): 89% Accuracy
- LGBM (Manual Features): 87% Accuracy

The combination of sentiment polarity and helpfulness scores improved drug ranking accuracy. SMOTE significantly enhanced recall on negative sentiment reviews, balancing model performance across classes.

The performance of the system was evaluated using the UCI Drug Review dataset. The dataset was cleaned, pre-processed, and split into training and testing sets for consistent model evaluation. Various classifiers were implemented, and their results were compared based on key evaluation metrics such as accuracy, precision, recall, and F1-score. Among the models used, LinearSVC with TF-IDF vectorization yielded the best results, achieving an accuracy of 93% and strong F1-scores for both positive and negative sentiment classes.

The Random Forest model performed well using a combination of Word2Vec embeddings and manual features, achieving 89% accuracy. LGBM performed slightly lower at 87% but demonstrated faster training time and scalability. The application of SMOTE significantly improved the recall score for minority classes, addressing class imbalance issues and ensuring fairer evaluation across sentiment types.

Furthermore, a scoring function was designed that combines sentiment prediction with normalized helpfulness scores. This dual-criteria ranking strategy improves the recommendation output by considering not just predicted sentiment, but also the reliability and usefulness of reviews as indicated by other users. A ranked list of top drugs for each condition is generated, offering users and clinicians practical suggestions backed by data-driven insights.

The system demonstrates robustness across various evaluation settings and shows promising potential for real-world deployment in digital healthcare platforms. Comparative analysis with baseline methods further validates the effectiveness of our hybrid approach in generating reliable drug recommendations.

X. 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, Linear SVC, applied on Bow, TF-IDF, and classifiers such as Decision Tree, Random Forest, Lgbm, and Cat boost were applied on Word2Vec and Manual features method. We evaluated them using five different metrics, precision, recall,

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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%), Linear SVC on TF-IDF (93%), LGBM on Word2Vec (91%), Random Forest on manual features (88%), and multiply them by the normalized useful Count to get the overall score of the drug by condition to build a recommender system. Future work involves comparison of different oversampling techniques, using different values of n-grams, and optimization of algorithms to improve the performance of the recommender system.

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