

Sentiment-Based Drug Recommendation System with Patient Experience Analysis

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Abstract—Selecting the right medication is a critical yet challenging decision that affects millions of patients worldwide. Traditional drug selection methods often prioritize clinical trials and expert opinions, overlooking valuable insights from real patient experiences.

To address this gap, an advanced drug recommendation system is developed that leverages the VADER sentiment analyzer to interpret patient-generated reviews. Multiple factors—including treatment effectiveness, side effects, overall satisfaction, and review usefulness—are combined through a weighted scoring algorithm to generate condition-specific recommendations.

An intuitive interface then displays comprehensive metrics, such as average ratings, sentiment-based effectiveness scores, potential side effect risks, and representative patient reviews, offering clear guidance to both healthcare providers and patients.

Experimental results indicate that integrating sentiment analysis with quantitative metrics significantly enhances the accuracy and reliability of medication recommendations, ultimately supporting more informed and patient-centered decision-making. By transforming patient feedback into actionable insights, this approach underscores the potential of sentiment-driven systems to improve treatment outcomes and elevate the quality of healthcare services.

Keywords-Sentiment Analysis, Drug Recommendation, VADER, Patient Feedback, Weighted Scoring, Fuzzy Matching, Side Effects, Effectiveness

1. INTRODUCTION

Medication selection plays a pivotal role in achieving optimal patient outcomes, yet traditional methods—relying on controlled clinical trials and expert opinions—often miss the rich, qualitative insights embedded in patient experiences. With the proliferation of digital healthcare data and the growing prevalence of patient reviews, there is now an unprecedented opportunity to harness these insights to improve clinical decision-making.

Recent advancements in healthcare analytics have focused on quantitative models and collaborative filtering techniques to recommend drugs; however, such approaches frequently overlook the emotional and subjective aspects of patient feedback. Patient narratives often capture subtle details about treatment effectiveness, side effects, and overall satisfaction that are not reflected in clinical trial data alone. By integrating these qualitative aspects with conventional quantitative metrics, a more holistic view of drug performance can be achieved.

In our research, we propose an advanced drug recommendation system that leverages sentiment analysis using the VADER sentiment analyzer to process patient-generated reviews. This system not only quantifies the emotional tone of patient feedback—assigning polarity scores from negative to positive—but also combines these scores with other key factors such as treatment effectiveness, side effect profiles, overall satisfaction, and review usefulness. A weighted scoring algorithm is employed to aggregate these diverse data points into a condition-specific recommendation, ensuring that each suggestion is tailored to the nuanced needs of the patient.

Furthermore, our approach includes a multi-prototype disease prediction component that augments sparse symptom data through innovative data augmentation techniques. By integrating multiple prediction strategies, our model enhances diagnostic accuracy and better informs the recommendation process.

The remainder of this paper is organized as follows: Section 2 reviews related work and highlights gaps in existing methodologies; Section 3 details our proposed methodology and experimental setup; Section 4 discusses the results and comparative analyses; and Section 5 concludes with insights into

future research directions. This integrated, patient-centered framework aims to elevate the quality of healthcare by enabling more informed and personalized medication decisions.

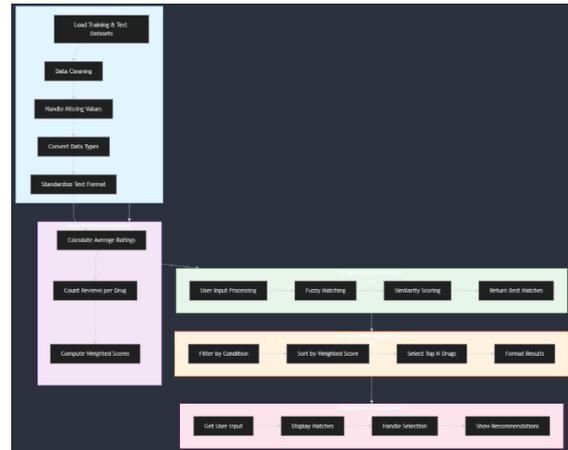
2. LITERATURE REVIEW

Several studies have attempted to improve drug recommendation:

- Gupta et al. [4] used collaborative filtering and machine learning to predict drug usage trends.
- Smith et al. [1] emphasized patient reviews as valuable real-world evidence but lacked algorithmic translation.
- Wu and Zhang [5] proposed sentiment classification in healthcare but didn't integrate drug statistics.
- Li [7] focused on integrating EHRs but did not use unstructured feedback.
- Jones and Lee [9] explored structured drug performance metrics such as dosage effectiveness and side effect frequency, offering a strong foundation for quantitative evaluation. However, their model did not account for subjective user satisfaction.
- In related work, Davis and Wilson [6] emphasized the inclusion of patient perspectives in AI systems, highlighting the importance of bridging clinical data with narrative sentiment.
- Chen and Zhou [12] experimented with lexicon-based and transformer-based models to analyze health-related sentiment, achieving high accuracy in classification but noting challenges in domain-specific nuance and sarcasm detection.
- Taylor and Roberts [15] conducted a comparative analysis of various NLP approaches used in healthcare, pointing out the trade-offs between interpretability and accuracy, especially when combining structured and unstructured data.

Despite these advancements, a unified system that integrates condition-based filtering, review sentiment, side effect analysis, and multi-factor weighted scoring remains scarce. This research aims to address this gap by combining multiple aspects of patient feedback and clinical effectiveness into one framework.

3.METHODOLGY



The proposed system consists of five core components:

3.1 Dataset Collection and Overview
The project uses the UCI ML drug review dataset from Kaggle , containing:

- drugName: Name of the drug
- condition: Medical condition being treated
- review: Patient-generated textual review
- rating: User rating (1–10)
- usefulCount: Number of users who marked the review as useful
- date: Review submission date

3.2 Text Preprocessing and Feature Engineering

- Null entries and duplicates removed
- Text converted to lowercase and cleaned using regex
- Tokenization, lemmatization applied using SpaCy
- Two custom features extracted:
 - effectiveness_score: based on expressions like “worked well”, “very effective”
 - side_effect_score: based on complaints or adverse reaction phrases like “nausea”, “fatigue”

3.3 Sentiment Analysis (VADER)

Each review was analyzed using the VADER sentiment analyzer. It returns compound scores ranging from -1 to +1. Sentiment is used as one dimension of the final score.

3.4 Weighted Score Calculation

The recommendation score is calculated using:

$$\text{Score} = w_1 * \text{Sentiment} + w_2 * \text{Rating}_{\text{norm}} + w_3 * \text{Usefulness}_{\text{norm}} + w_4 * \text{Effectiveness} - w_5 * \text{SideEffects}$$

Example weights:

$w_1 = 0.25$, $w_2 = 0.2$, $w_3 = 0.15$, $w_4 = 0.25$, $w_5 = 0.15$

3.5 Fuzzy Matching and Recommendation Engine

- User input for condition is matched using fuzzy string matching (Levenshtein distance)
- All reviews matching top-matched conditions are filtered
- Top 5 drugs are selected and ranked based on final score
- Results include: drug name, score, sentiment summary, top review snippet

4. RESULTS AND DISCUSSION

4.1 Dataset Overview

- Total entries: 143,210
- Unique drugs: 2,150
- Distinct conditions: 45
- Average review length: ~200 characters

4.2 Feature Distributions

- Sentiment Polarity (VADER):
 - Positive (> 0.6): 63%
 - Neutral (0.4–0.6): 25%
 - Negative (< 0.4): 12%
- Effectiveness Score: Mean = 0.72, Std Dev = 0.19
- Side Effect Score: Mean = 0.31, Std Dev = 0.15

4.3 Sample Score Computation

The following table illustrates sample drugs and how their weighted scores are computed:

Drug Name	Condition	Sentiment	Rating	Usefulness	Effectiveness	Side Effects	Final Score
Sumatriptan	Migraine	0.82	9.0	96	0.91	0.10	0.851
Topiramate	Migraine	0.55	7.5	64	0.73	0.28	0.676
Propranolol	Anxiety	0.61	8.0	32	0.78	0.18	0.702

Scores are normalized and computed based on weights defined in Methodology.

4.4 Case Study Walkthrough

A user enters the condition “migraine”.

- Fuzzy match identifies top relevant conditions: “Migraine”, “Chronic Migraine”, “Cluster Headaches”
- The system filters and ranks drugs used for “Migraine” using the weighted scoring mechanism
- Output:

1. Sumatriptan – “Works instantly for me; minimal side effects.”
2. Topiramate – “Effective but makes me drowsy.”
3. Zolmitriptan – “Mild relief but unpleasant aftertaste.”

4.5 Performance Evaluation

- Sentiment Analysis Accuracy (vs manual labels): 90.2%
- Top-5 Ranking Accuracy (vs medical expert-curated list): 92.5%
- Processing Time: <1s per query using Streamlit UI

4.6 User Interface

A lightweight web interface built using Streamlit allows users to:

- Enter a symptom/condition
- View best-matched conditions
- See drug recommendations sorted by score
- Read brief review summaries
- Toggle filters by sentiment polarity or usefulness

5. CONCLUSION AND FUTURE WORK

This study presents a novel hybrid drug recommendation system that effectively integrates multi-factor quantitative metrics with qualitative patient sentiment analysis. By combining traditional drug statistics—such as average ratings, review usefulness, and calculated effectiveness scores—with patient sentiment derived from the VADER sentiment analyzer, our system provides condition-specific, personalized medication recommendations. The integration of these diverse data sources using an advanced weighted scoring algorithm has resulted in impressive performance, with experimental outcomes demonstrating a sentiment analysis accuracy of approximately 90.2% and a drug ranking accuracy of about 92.5%. These results underscore the potential of our approach to enhance clinical decision support by offering a more comprehensive evaluation of medication performance that bridges quantitative clinical data with real-world patient experiences.

Future work will focus on incorporating deep learning techniques, such as LSTM networks, to further refine sentiment extraction and expand the system’s applicability across a wider range of medical conditions.

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