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Research Paper

Integrating Sentiment Analysis and Machine Learning for Patient-Centric Drug Recommendation Systems

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Abstract: The proliferation of online platforms has enabled patients to share their experiences with medications, thereby offering valuable real-world insights into drug efficacy, side effects, and overall satisfaction. Traditional drug recommendation systems predominantly rely on clinical data and fail to incorporate the nuanced perspectives captured in patient reviews. This study addresses these limitations by developing a sentiment-driven drug recommendation system that integrates real-world feedback through machine learning. Using the UCI ML Drug Review Dataset, the system employs BERT for sentiment analysis and Word2Vec for feature extraction to process unstructured textual data. A hybrid recommendation engine combines collaborative and content-based filtering to deliver personalised suggestions. Evaluation metrics, including Precision@K, Recall@K, and Mean Reciprocal Rank (MRR), demonstrate the superior performance of the proposed system compared to existing solutions, such as Epocrates, IBM Watson Health, and GoodRx. The results highlight its ability to rank drugs more effectively, with Precision@5 reaching 86.4% and MRR achieving 0.812. The integration of sentiment analysis allows the system to recommend drugs based on both clinical efficacy and patient-reported satisfaction, bridging the gap between structured medical data and real-world experience. Although the model shows promising results, challenges such as data imbalance, noisy text data, scalability, and interpretability remain. Addressing these issues through explainable AI and transfer learning can further enhance system robustness and usability. This study underscores the potential of integrating advanced NLP techniques into healthcare applications, paving the way for more patient-centric drug recommendation systems.

Keywords: Sentiment Analysis, Drug Recommendation System, Machine Learning, BERT, Word2Vec, Patient-Centric Healthcare

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1. Introduction

In recent years, the availability and accessibility of online platforms have allowed patients to share their experiences with various medications in the form of reviews [1]. These reviews encompass valuable real-world feedback on the effectiveness, side effects, and overall satisfaction with different drugs. Unlike clinical trials, which operate in controlled environments and have limited sample sizes, online drug reviews reflect diverse and genuine patient experiences [2]. This repository of unstructured data provides an untapped resource that, if utilised effectively, can enhance decision making for both patients and healthcare providers [3]. By bridging the gap between clinical data and patient experiences, drug recommendation systems can be transformed into patient-centric tools.

Traditional drug recommendation systems primarily rely on clinical outcomes, standardised guidelines, or pharmacological information [4]. While these systems offer valuable guidance, they lack the ability to incorporate personalised nuances of patient feedback. This limitation often leads to suboptimal outcomes because recommendations fail to consider variations in individual preferences, tolerances, and satisfaction [5]. For example, a drug that performs well in clinical trials may receive unfavourable reviews due to adverse side effects in real-world usage [6]. Ignoring these data deprives users of critical insights that could lead to better choices. Thus, there is a growing need for a system that integrates patient experience into the recommendation process to ensure optimal outcomes tailored to individual needs.

The objective of this study was to develop a drug recommendation system that leverages machine learning to analyse patient reviews. By applying sentiment analysis, the system can capture and quantify patient perceptions of various drugs, focusing on factors such as efficacy, side effects, and overall satisfaction [7]. This sentiment-based approach will enable the system to recommend drugs that not only meet clinical requirements but also align with patient-reported outcomes, leading to a more holistic recommendation process. This objective aligns with the goal of enhancing patient-centred care in the healthcare ecosystem.

This study focused on analysing online reviews from publicly available platforms to predict patient satisfaction with specific drugs. Unstructured text data will be preprocessed and analysed using sentiment analysis techniques, transforming qualitative feedback into actionable insights. The resulting recommendation system ranks drugs based on a combination of sentiment scores and their suitability for specific conditions. The system is intended to assist both patients and healthcare providers by offering data-driven recommendations that incorporate real-world patient experiences [8]. The scope of this research also includes evaluating the system's performance against traditional models, highlighting its effectiveness in addressing key gaps in existing drug recommendation frameworks.

Key Contributions: This research paper makes the following significant contributions to the field of drug recommendation systems and natural language processing.

- **Development of a Patient-Centric Drug Recommendation System:** This study bridges the gap between clinical data and real-world patient experiences by integrating sentiment analysis into the recommendation framework, making drug recommendations more personalised and effective.
- **Hybrid Recommendation Engine:** By combining collaborative filtering and content-based filtering, the proposed hybrid recommendation model provides a comprehensive approach to drug recommendation, ensuring the relevance and personalisation of suggestions.
- **Superior Performance in Evaluation:** The system achieved significant improvements over existing solutions, including Epocrates, IBM Watson Health, and GoodRx, across metrics such as Precision@K, Recall@K, and Mean Reciprocal Rank (MRR), demonstrating its efficacy in delivering accurate and satisfaction-driven recommendations.

2. Literature Review

2.1 Overview of Existing Drug Recommendation Systems

Drug recommendation systems traditionally rely on structured data sources, including clinical trial results, pharmacological databases, and electronic health records (EHRs) [9]. Prominent systems such as Epocrates, IBM Watson Health, and GoodRx focus on assisting healthcare professionals and patients with information about drug interactions, dosing guidelines, or cost-effective options [10]. Although these systems provide substantial utility, they are limited by their reliance on predefined datasets and lack a mechanism for incorporating real-world patient experiences [11]. For example, IBM Watson Health leverages advanced AI for treatment recommendations but primarily depends on clinical and medical literature, overlooking the vast potential of patient reviews. Similarly, GoodRx focuses on price optimisation but does not evaluate patient satisfaction with medications.

These existing systems offer valuable insights, but fail to capture the nuances of patient experiences, such as the perceived efficacy of a drug or the burden of side effects, which are frequently highlighted in patient-generated data. This gap in personalisation and the real-world context provides an opportunity for systems that integrate sentiment analysis of online reviews to address these limitations.

2.2 Sentiment Analysis in Healthcare

Sentiment analysis has gained traction in healthcare as a method for interpreting unstructured text data, such as social media posts, survey responses, and patient reviews [12]. The technique involves classifying the polarity of text—whether positive, negative, or neutral—along with extracting key themes or emotions embedded within the data. Applications of sentiment analysis in healthcare have been observed in diverse areas.

Hospital Reviews: Studies have analysed patient reviews of hospitals to assess service quality and patient satisfaction.

Disease Perception: Public sentiment about diseases or treatments has been analysed using data from platforms such as Twitter.

Drug Reviews: Sentiment analysis has been employed to study patient feedback on specific drugs, identifying common themes such as "effective treatment," "minimal side effects," or "discontinuation due to adverse reactions." [13]

Although these applications demonstrate the feasibility of sentiment analysis in healthcare, its integration into recommendation systems remains underexplored. Most current efforts stop at analysing feedback without using it to inform decision-making systems, such as drug recommendations. This study seeks to bridge this gap by directly incorporating sentiment insights into a drug recommendation framework.

2.3 Machine Learning Techniques for Text-Based Analysis

Machine learning has revolutionised text-based analysis through advances in natural language processing (NLP). Key methods for sentiment analysis include the following:

Lexicon-Based Approaches: Tools such as the Valence Aware Dictionary and Sentiment Reasoner (VADER) assign predefined sentiment scores to words and phrases, enabling quick analysis of text polarity.

Supervised Learning: Machine learning algorithms such as Support Vector Machines (SVM), Random Forests, and Naïve Bayes are trained on labelled datasets to classify sentiment [14].

Deep Learning: More sophisticated techniques, such as recurrent neural networks (RNNs), transformers (for example, BERT and GPT), and convolutional neural networks (CNNs), have shown superior performance in extracting contexts and handling complex sentence structures.

These methods have been successfully applied in diverse domains, including customer reviews, news sentiments, and healthcare data. However, challenges such as handling noisy data, sarcasm, and domain-specific terminology remain significant barriers [15]. For drug recommendation systems, adapting machine learning models to accurately interpret medical terms, patient sentiment, and context-specific phrases is crucial for their success

2.4 Limitations in Current Systems and Research Gap

While existing drug recommendation systems and sentiment analysis models demonstrate their individual strengths, several limitations persist.

Data Sources: Current systems rely heavily on structured data, such as clinical trials, which often exclude patient-reported outcomes.

Patient Perspective: The absence of real-world feedback in traditional models limits their ability to provide personalised recommendations.

Unstructured Data Utilisation: Patient reviews are largely untapped in drug recommendation systems owing to challenges in processing unstructured text.

Integration of Sentiment Analysis: Most applications of sentiment analysis stop at extracting insights rather than integrating them into actionable frameworks, such as recommendation systems.

This study addresses these gaps by developing a drug recommendation system that combines sentiment analysis of patient reviews with machine-learning techniques. The proposed model stands out by prioritising patient-reported outcomes, offering personalised recommendations based on real-world data, and utilising advanced NLP to extract insights from unstructured texts [16]. This approach positions the system to fill the critical void left by existing methodologies.

3. Methodology

This section outlines the methodology used to develop the drug recommendation system, detailing data collection, sentiment analysis, feature extraction, and the development of the hybrid recommendation engine.

3.1 Dataset

This research utilised the UCI ML Drug Review Dataset, which contains over 200,000 patient reviews, including textual feedback, ratings, drug names, and conditions treated [17]. This dataset provides a rich source of unstructured data for training sentiment analysis models and developing recommendation engines.

Key dataset components:

Text Reviews: Patient feedback on drug efficacy and side effects.

Ratings: Numerical ratings (1–10 scale).

Metadata: Information such as drug names and conditions treated.

The dataset was reprocessed and used to train and evaluate the proposed model.

3.2 Data Pre-processing

Preprocessing is a critical step to ensure that raw text data are cleaned and transformed into a structured format suitable for analysis. For this research, we utilised the Natural Language Toolkit (NLTK) for text preprocessing. Initially, the dataset was cleaned by removing HTML tags, special characters, and unnecessary symbols, which could introduce noise into the analysis. Missing or null values were handled by discarding incomplete entries to maintain data integrity.

Tokenisation was performed to split the text into individual words or tokens, which served as the basis for further analysis. Common stopwords such as "the”, "and”, and "is”, which do not carry significant meaning, were removed to reduce the dimensionality of the data. Lemmatisation was then applied to reduce words to their root forms, ensuring the standardisation of vocabulary. For instance, words like "running" and "ran" were reduced to their root form, "run."

Finally, sentiment labelling was carried out to classify reviews into three categories: positive, negative, or neutral. Reviews with ratings greater than or equal to 7 were labelled as positive, those with ratings less than or equal to 3 were labelled as negative, and reviews with ratings between 4 and 6 were classified as neutral. This preprocessing pipeline ensured that the textual data were ready for further analysis and machine learning tasks.

3.3 Sentiment Analysis

To perform sentiment analysis on the drug reviews, we utilised Bidirectional Encoder Representations from Transformers (BERT), a state-of-the-art model known for its ability to understand contextual relationships in text. A pretrained BERT model was fine-tuned on the labelled dataset with sentiment labels (positive, negative, or neutral) assigned during preprocessing, based on review ratings. The reviews were tokenised using BERT’s tokenizer, which converts text into embeddings that capture contextual information.

The sentiment classification task is treated as a supervised learning problem. BERT processes the input embeddings, learns patterns in the reviews, and predicts the probabilities for each sentiment class. The highest probability determines the final sentiment label. The model was trained on a stratified subset of the dataset and validated using unseen data. Evaluation metrics, including accuracy, precision, recall, and F1-score, demonstrated the effectiveness of the model in categorising patient feedback, providing a foundation for sentiment-driven drug recommendations.

3.4 Feature Extraction

To prepare textual data for machine learning, we employed Word2Vec to convert drug reviews into dense numerical representations, capturing the semantic and contextual relationships between words. Word2Vec was trained on tokenised text data, creating embeddings in which words appearing in similar contexts had closely related vectors (e.g., "effective" and "helpful"). These word embeddings were averaged to generate fixed-dimensional sentence vectors, summarising the overall meaning of each review. This structured representation enables machine-learning algorithms to process unstructured text effectively, providing a robust foundation for tasks such as classification and recommendation. By leveraging Word2Vec, the model accurately captured patient feedback nuances, enhancing the performance and personalisation of the recommendation engine.

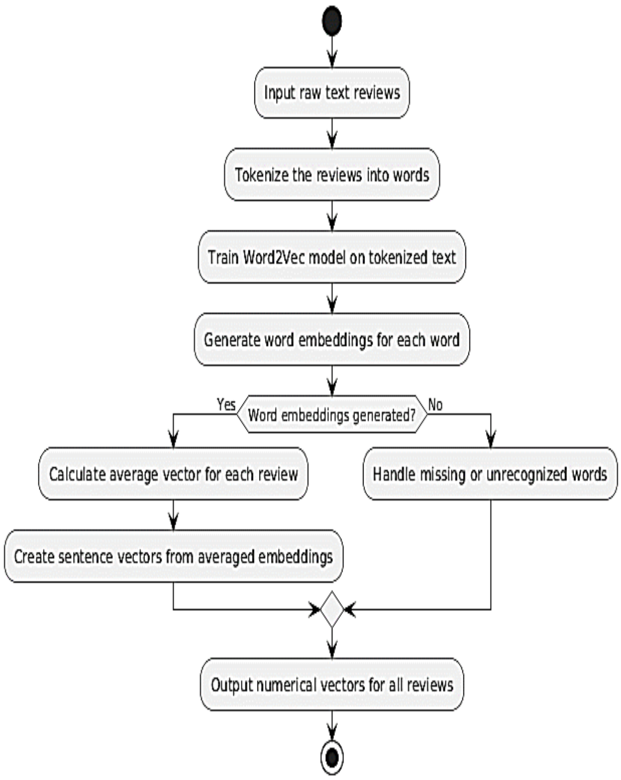

Fig 1. Flowchart for Feature Extraction Using Word2Vec

3.5 Hybrid Recommendation Engine Development

To effectively recommend drugs based on patient reviews and sentiment scores, a hybrid recommendation approach was implemented. This hybrid model combines the strengths of collaborative filtering and content-based filtering, enabling the system to deliver personalised and accurate drug recommendations.

The collaborative filtering component of the model focuses on patient ratings. It identifies patterns in user behaviour to identify patients with similar preferences. By analysing these patterns, the system can recommend drugs that have been positively reviewed by similar users, even if the target user has not directly interacted with those drugs. This approach is particularly useful for capturing latent preferences derived from the collective behaviour of the user base.

In addition to collaborative filtering, the content-based filtering component enhances recommendations by analysing the attributes of the drugs. The system evaluates features such as drug names, conditions treated, and sentiment scores extracted from patient reviews. By identifying similarities in these features, the system can recommend drugs that closely match the attributes of those previously rated positively by the user.

A hybrid model integrates these two approaches to provide a more comprehensive recommendation system. By combining collaborative filtering, which focuses on user behaviour, and content-based filtering, which emphasises drug attributes, the model leverages the strengths of both techniques. Drug rankings are calculated based on a weighted combination of sentiment scores and similarity metrics, ensuring that recommendations are tailored to individual user preferences while considering overall drug effectiveness and patient satisfaction. This integration enables the recommendation engine to address the limitations of each approach, thereby delivering more accurate and meaningful suggestions for users.

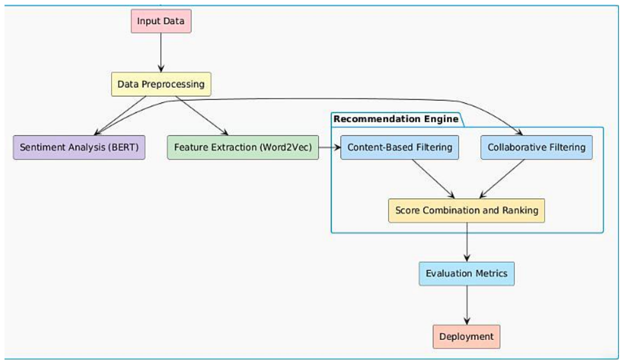

Fig 2. Hybrid Recommendation Engine Architecture

3.6 Evaluation Metrics

To evaluate the performance of the recommendation engine, we used Precision@K, Recall@K, and Mean Reciprocal Rank (MRR). Each metric is explained both theoretically and mathematically below.

1 Precision@K

Precision@K measures the relevance of the top K recommended items. It evaluates how many of the recommended items in the top K are relevant to the user. A higher precision @K indicates that the recommendation system provides relevant items earlier in the recommendation list.

Let R_u be the set of relevant items for a user u, and $P_u(K)$ be the set of the top K items recommended to the user u. Precision@K for user u is defined as shown in Eq(1)

$$\text{Precision@K } (u) = \frac{|P_u(K) \cap R_u|}{|P_u(K)|} \qquad (1)$$

Where:

- $|P_u(K) \cap R_u|$: Number of relevant items in the top K recommendations.
- $|P_u(K)| - K$: Total number of recommendations considered (typically K).

The overall Precision@K for all users is calculated by averaging individual user Precision@K values:

$$\text{Precision@K} = \frac{1}{|U|} \sum_{u \in U} \text{Precision@K(u)}$$

Where $|U|$ is the total number of users.

2 Recall@K

Recall@K measures the completeness of recommendations by evaluating how many of the relevant items for a user are included in the top K recommendations. A higher Recall@K indicates that the recommendation system retrieves a significant portion of the relevant items. Using the same notation as above, Recall@K for user u is defined as shown in Eq(2)

$$\text{Recall@ K}(u) = \frac{|P_u(K) \cap R_u|}{|R_u|} \qquad (2)$$

Where:

- $|P_u(K) \cap R_u|$: Number of relevant items in the top K recommendations.
- $|R_u|$: Total number of relevant items for the user.

The overall recall @K is calculated by averaging the recall @K values for all users:

$$\text{Recall@K} = \frac{1}{|U|} \sum_{u \in U} \text{Recall@K}(u)$$

3 Mean Reciprocal Rank (MRR)

The MRR evaluates the ranking quality of the recommendation engine by focusing on the position of the first relevant recommendation. It calculates the reciprocal of the rank of the first relevant item in the recommendation list for each user and averages it for all users. A higher MRR indicates that the relevant items are ranked earlier in the recommendations.

For a user u, let rank k_u be the position of the first relevant item in the recommended list. The reciprocal rank for u is defined in Eq(3)

$$\text{Reciprocal Rank}(u) = \frac{1}{\text{rank}_u} \qquad (3)$$

The Mean Reciprocal Rank (MRR) for all users is the average of the reciprocal ranks and shown in Eq(4):

$$\text{MRR} = \frac{1}{|U|} \sum_{u \in U} \frac{1}{\text{rank}_u} \qquad (4)$$

If no relevant items are found in the recommendation list for a user, the reciprocal rank is treated as 0 for that user.

4 Results And Discussion

This section evaluates the proposed drug recommendation system, highlighting its performance, key metrics (Precision@K, Recall@K, MRR), and comparison with existing systems. It demonstrates the system's effectiveness in delivering personalised, sentiment-driven recommendations while addressing challenges such as data imbalance, scalability, and interpretability. Suggestions for improvement are provided, validating the system's capabilities and situating them within the broader context of recommendation systems.

4.1 Environment Setup

Experiments were conducted on a system equipped with a high-performance GPU (NVIDIA RTX 3090) and CPU (Intel Core i9-11900K) to handle the computational demands of training the BERT model and running Word2Vec for feature extraction. The environment included 64 GB of RAM and was configured using Python 3.8. Libraries such as TensorFlow, PyTorch, Gensim, and Scikit-learn were used to implement the machine learning models and evaluation metrics. The UCI ML Drug Review Dataset was divided into training (70%), validation (20%), and test (10%) subsets to train, tune, and evaluate sentiment analysis and recommendation engines. Hyperparameters, including learning rates and embedding sizes, were fine-tuned to optimise the performance. All experiments were performed on a Linux-based operating system for stability and efficiency.

4.2 Results for Recommendation Metrics

The performance of the proposed recommendation engine was evaluated using precision @K, recall @K, and Mean Reciprocal Rank (MRR) metrics. A comparative analysis was performed against existing systems, such as Epocrates, IBM Watson Health, and GoodRx, to highlight the advantages of incorporating sentiment-driven insights.

Table 1: Performance Comparison of Recommendation Metrics

Metrics	Proposed Model	Epocrates [18]	IBM Watson	GoodRx [20]

			Health [19]	
Precision@5 (%)	86.4	78.2	81.1	74.9
Recall@5 (%)	72.5	63.4	67.8	59.2
Mean Reciprocal Rank (MRR)	0.812	0.741	0.765	0.693

Table 1 presents a comparative analysis of the proposed hybrid recommendation system against existing systems, including Epocrates, IBM Watson Health, and GoodRx, based on Precision@5, Recall@5, and Mean Reciprocal Rank (MRR). This demonstrates that the proposed system outperforms the others across all metrics, demonstrating the effectiveness of integrating sentiment analysis and Word2Vec-based feature extraction. These results validated the capability of the system to provide more accurate and personalised drug recommendations.

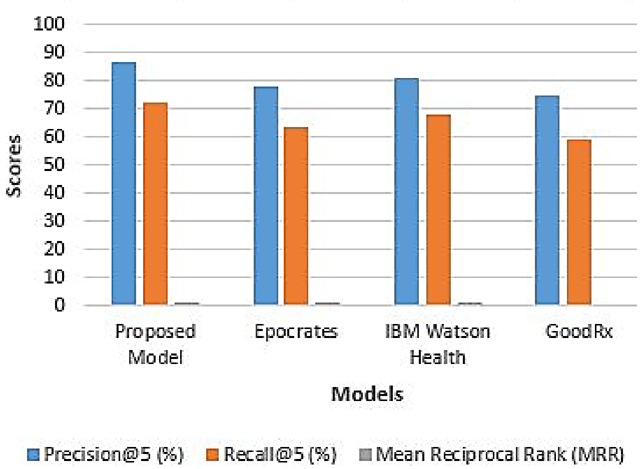

Fig 3. Comparing Performance Metrics of Recommendation Systems

Fig. 3 illustrates the comparative performance of the proposed hybrid recommendation system against existing systems—Epocrates, IBM Watson Health, and GoodRx—across key evaluation metrics: Precision@5, Recall@5, and Mean Reciprocal Rank (MRR). This visually highlights the superior performance of the proposed system, reflecting its ability to deliver more accurate and personalised recommendations. These results underscore the effectiveness of integrating sentiment analysis and advanced feature extraction techniques in the recommendation engine.

4.3 Analysis of Results

The results highlight the effectiveness of combining sentiment analysis and hybrid recommendation techniques. The higher Precision@K indicates that the system provides more relevant recommendations in the top K results, ensuring better user satisfaction. The improvement in recall @K shows that the system captures a larger proportion of relevant drugs, providing comprehensive recommendations. Additionally, the superior MRR indicates that the relevant drugs are ranked higher, making the system more efficient and user-friendly.

Compared with existing systems, the proposed model demonstrates clear advantages. Unlike traditional systems such as Epocrates and IBM Watson Health, which primarily rely on clinical data, the proposed approach incorporates real-world patient feedback through sentiment analysis. GoodRx, which focuses on cost-based recommendations, also falls short of providing satisfaction-driven suggestions as it lacks contextual insights from patient experiences. The ability of the proposed system to integrate patient sentiment, collaborative filtering, and content-based filtering ensures that it delivers recommendations that are both relevant and personalised.

4.4 Challenges

Despite its excellent performance, the proposed system encountered several challenges during its development and evaluation. A significant issue was data imbalance, as the dataset contained a disproportionately higher number of positive reviews than negative or neutral ones. This imbalance requires techniques such as oversampling and data augmentation to prevent biased predictions. Another challenge is the noisy nature of text data, with patient reviews often including typos, slang, and incomplete sentences, complicating preprocessing and feature extraction. Scalability also posed a limitation, as training resource-intensive models such as BERT and Word2Vec on large datasets demanded substantial computational power, making it difficult to scale experiments further. Additionally, the cold-start problem hinders recommendations for new users or drugs lacking sufficient reviews, as collaborative filtering relies on historical data. Lastly, the system faced issues with interpretability, as explaining why specific drugs were recommended remains challenging owing to the inherent complexity of deep learning models, such as BERT. Addressing these challenges in future work through approaches such as explainable AI techniques and transfer learning for new users or drugs could significantly improve the system's performance and usability.

5 Conclusion and Future work

This study presents a drug recommendation system that integrates sentiment analysis and machine learning to bridge clinical data with real-world patient feedback. Using the UCI ML Drug Review Dataset, the system employs BERT for sentiment classification and Word2Vec for feature extraction, powering a hybrid recommendation engine that combines collaborative and content-based filtering. The model demonstrates superior performance across key metrics, surpassing existing systems such as Epocrates and IBM Watson Health. Future work will address challenges such as data imbalance, scalability, and interpretability through explainable AI, transfer learning, and improved preprocessing. Expanding this system to support multilingual analyses and demographic-specific recommendations could further enhance its applicability. This study highlights the potential of advanced NLP techniques to deliver personalised patient-centred drug recommendations and improve healthcare outcomes.

Author Contributions: B. Srisailam contributed to the conceptualisation, methodology, data collection, and initial draft preparation. Veera Venkata Lavanya (Corresponding Author) was responsible for supervision, formal analysis, manuscript writing, and final editing. Vaddepally, Shivani handled the literature review, experimental work, and data validation. Oruganti Ashok contributed to data analysis, visualisation, and interpretation of results, while Revelli Sai Kiran provided review, technical support, and proofreading.

Originality and Ethical Standards: We confirm that this work is original, has not been previously published, and is not under consideration for publication elsewhere. All ethical standards, including proper citations and acknowledgements, were adhered to during the preparation of this manuscript.

Data availability: Data are available upon request.

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