© May 2025| IJIRT | Volume 11 Issue 12 | ISSN: 2349-6002

Advancing e-Health: A Hybrid AI-Powered Chatbot for Personalized Medicine Recommendation

Aaryan Maheshwari[1], Dipanshu Mundeja[2], Dr. S.Girirajan[3], Dr. Sandhia G K[4], Dr. M Karthikeyan[5]
Department of CTech SRMIST Chennai, Tamil Nadu
Department of CTech, SRMIST Chennai, Tamil Nadu
Assistant Professor, Department of CTech, SRMIST, Chennai, Tamil Nadu
Associate Professor, Department of CTech, SRMIST, Chennai, Tamil Nadu
Assistant Professor, Department of CTech, SRMIST, Chennai, Tamil Nadu

Abstract - In the advanced landscape of healthcare technology, the precision and personalization of medicinal recommendations are crucial for improving patient outcomes. This paper introduces a novel hybrid recommendation system encapsulated within a chatbot that not only suggests medicines based on patient-reported symptoms but also generates tailored prescription details. Utilizing a robust combination of content-based filtering, employing cosine similarity, and collaborative filtering through Singular Value Decomposition (SVD), the system excels in offering highly accurate medicine suggestions with similar chemical compositions. Enhanced by a comprehensive dataset from Kaggle, the chatbot integrates innovative user-friendly features that facilitate seamless interaction with established online pharmaceutical platforms. This research thoroughly examines the chatbot's architecture and user interaction design, demonstrating significant enhancements in delivering personalized healthcare recommendations. The integration of prescription support into the chatbot further augments its utility, making it a critical tool in the digital healthcare ecosystem. This study underscores the effectiveness of hybrid filtering approaches and sets a new benchmark for intelligent recommendation systems in medicine.

I. INTRODUCTION

In the rapidly evolving domain of digital healthcare, the ability to deliver precise and personalized medicine recommendations is not just a technological advancement but a necessity for improving patient care and treatment outcomes. Traditional recommendation systems, though foundational, frequently fall short in providing tailored and accurate medical advice, critical in scenarios where the stakes involve human health. Such systems often rely on simplistic or generic algorithms that do not account for the unique complexities of individual patient needs and the nuanced differences between medications.

Recognizing these challenges, this study introduces a sophisticated hybrid recommendation system designed to transcend the limitations of conventional methodologies. By integrating content-based filtering (CBF) with collaborative filtering (CF), our approach not only leverages the detailed attributes of medicines, such as their chemical properties, but also incorporates user feedback and historical data to enhance the personalization of recommendations. The innovation at the core of our system is the prioritization of content-based recommendations, utilizing cosine similarity and Singular Value Decomposition (SVD) to refine the accuracy with which medicines are suggested.

The primary aim of this research is to revolutionize the field of medicine recommendation by significantly boosting the precision and relevance of the suggestions provided. With a focus on content-based filtering enhanced by cosine similarity, our system is uniquely capable of identifying and recommending medications with similar chemical compositions, thereby ensuring more targeted and effective treatment options tailored to individual patient profiles. This approach not only caters to the immediate health requirements of patients but also paves the way for a more intuitive, responsive, and patient-centered healthcare technology landscape.

II. LITERATURE SURVEY

Advancements in Collaborative Filtering: Factorization Machines (FMs) represent a significant breakthrough in collaborative filtering technologies. These models handle sparse datasets efficiently, making them highly effective for user-item interaction in recommendation systems. Their ability to integrate diverse data types enhances their application in predicting user preferences for specific medicines based on historical data ar5iv.org

Content-Based Filtering Innovations: The integration of content-based filtering with advanced neural network architectures has led to more precise medicine recommendations. Techniques such as capsule neural networks and convolutional neural networks have been employed to analyze medical data deeply, allowing for the extraction of complex features such as patient demographics, symptoms, and medical history, which significantly improve the accuracy of medicine recommendations ijrar.org

Hybrid Systems for Enhanced Accuracy: Combining content-based and collaborative filtering, recent hybrid recommendation systems utilize both user behavioral data and item (medicine) attributes to make more accurate predictions. This dual approach leverages the strengths of both systems to recommend medicines that are not only similar chemically but also proven effective for patients with similar profiles ijraset.com

Inclusion of Chatbot Features: The addition of a chatbot interface significantly enhances user interaction within medicine recommendation systems. Chatbots facilitate real-time data input and feedback, allowing patients to input symptoms and receive personalized medicine recommendations instantly. This feature not only improves user engagement but also aids in collecting real-time data that can be used to refine recommendation algorithms continuously. Implementing natural language processing (NLP) techniques within chatbots further enables them to understand and process user queries more effectively, making the system more intuitive and accessible to users without medical expertise ijraset.com

Real-World Application and User Interface: The practical implementation of these systems in a clinical setting involves sophisticated front-end technologies like HTML, CSS, and jQuery for creating responsive and interactive user interfaces. These interfaces allow healthcare providers and patients to interact seamlessly with the system, entering symptoms and viewing personalized medicine recommendations. The backend, often developed in Python using libraries like Scikit-learn and Pandas, supports the complex computational processes required to analyze medical data and generate accurate recommendations

III. PROPOSED METHODOLOGY

A hybrid recommendation system combines the strengths of CBF and CF to overcome these limitations. By leveraging both item features and user interactions, the hybrid approach can address the cold start problem and improve recommendation accuracy in sparse data settings.

Content-Based Filtering: Cosine Similarity Algorithm The cosine similarity algorithm measures the similarity between two items based on their vector representations. A higher cosine value signifies a greater similarity between the items.

$$\text{cosine similarity} = \cos(\theta) = (A \cdot B) / ||A||\ ||B||$$

where:

A and B represent the vectors to compare denotes the vector dot product ||A|| and ||B|| represent the magnitudes of vectors A and B

To generate the cosine similarity vector for an item, the algorithm first extracts relevant features from the item, such as keywords, genre, or product description. These features are then represented as a vector. The cosine similarity between the item vector and the vectors of other items is calculated, resulting in a cosine similarity vector.

Collaborative Filtering: SVD Algorithm

The singular value decomposition (SVD) algorithm is a popular CF technique that can handle large and sparse datasets. It decomposes the user-item interaction matrix into three matrices:

$$X = U\Sigma V^T$$

where:

X represents the user-item interaction matrix U represents the user matrix Σ represents the singular values matrix V represents the item matrix

The SVD algorithm reduces the dimensionality of the user-item interaction matrix, making it more manageable and improving computational efficiency. The user and item matrices can then be used to predict missing interactions or generate recommendations.

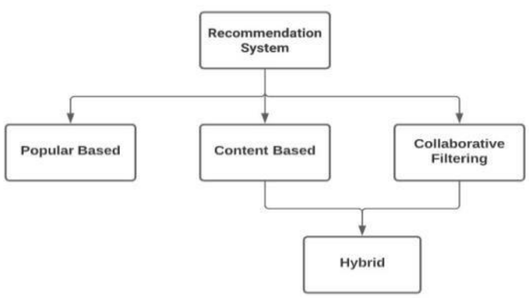

Fig. 3.1 Recommendation System

Requirement Gathering

User Interface Design: The system's interface is designed to be highly intuitive and user-centric, enabling effortless interaction. The chat interface, which acts as the primary user interaction point, allows patients to input symptoms and receive medication recommendations seamlessly. This ensures that the system is accessible to a broad user base, including those unfamiliar with medical terminology.

Type and Search Capability: The chatbot feature is equipped with natural language processing (NLP) capabilities, allowing users to type in their symptoms or search for specific medicines. This functionality enhances the system's usability, making it a practical tool for diverse user needs.

Advanced Recommendation Engine: At the heart of the system is a sophisticated recommendation engine that employs a hybrid approach, combining content-based and collaborative filtering. This engine is designed to adapt to evolving user preferences and effectively utilize vast datasets to generate personalized medicine suggestions.

E-Commerce Integration: Strategic integration with online pharmaceutical platforms like Pharmeasy and Netmeds streamlines the procurement process. Users can transition smoothly from receiving recommendations to purchasing medications, enhancing the overall user experience.

Data Foundation: The system utilizes the "Medicine Recommendation Dataset" available on Kaggle. This comprehensive dataset provides a robust foundation for training and evaluating the recommendation algorithms.

Operational Steps:

1. Data Collection:
   - Data is sourced from pharmaceutical databases, drug descriptions, and user interaction data, including reviews and purchase histories.
2. Data Preprocessing:
   - The preprocessing phase addresses inconsistencies and prepares the data for analysis. This includes cleaning, normalization, and text processing to convert medical descriptions into structured formats.
3. Similarity Calculation (Content-Based Filtering):
   - Medicines are converted into vector representations using techniques like TF-IDF or advanced embeddings (e.g., BERT). Cosine similarity is calculated to identify medicines with similar properties, facilitating targeted recommendations.
4. User-Item Matrix Creation (Collaborative Filtering):
   - A matrix capturing user interactions with medicines is built. Techniques such as SVD or Matrix Factorization are applied to handle sparsity and derive latent features that inform user preferences.

5. Hybrid Method Integration:
   - The system combines content-based and collaborative results using methods like weighted hybrids or stacking ensemble models. This ensures comprehensive coverage across different user interaction levels.
6. Deployment:
   - The model is deployed using applications like Streamlit, which supports both the backend recommendation logic and the frontend user interface.

Chatbot Integration: The inclusion of a chatbot enhances real-time interaction capabilities. Equipped with NLP, the chatbot efficiently handles queries about symptoms and medications, providing instant and accurate recommendations based on user inputs. This feature not only improves engagement but also continuously refines the recommendation process based on user feedback.

Technical Architecture: The architecture diagram of the system illustrates the seamless integration of content-based and collaborative filtering methods, with a significant emphasis on the chatbot interface to ensure dynamic and responsive user interactions.

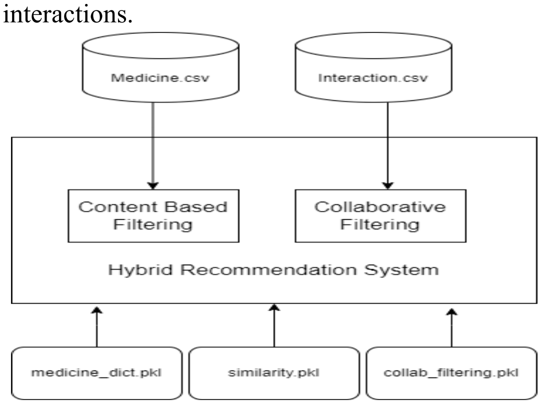

Fig. 3.1 Architecture Diagram

State Chart Diagram: To visually depict the system's behaviour, we utilize a state chart diagram. This diagram outlines the different states and transitions within the system, providing a clear and intuitive representation of its operations and how it adapts to user interactions.

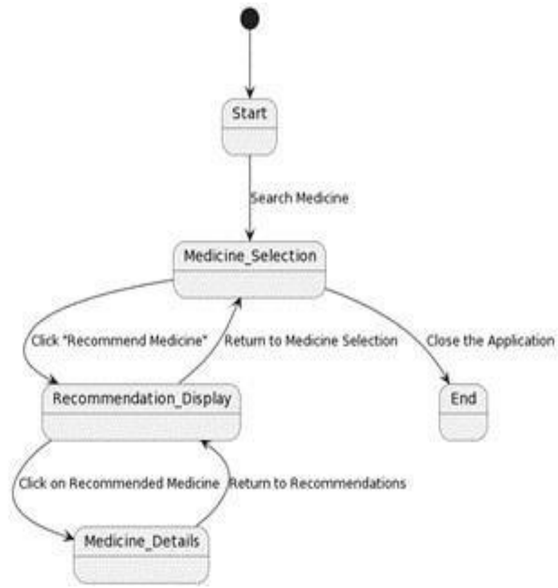

Fig. 3.5 State Chart Diagram

IV. RESULTS & DISCUSSIONS

1. Evaluation:

Accuracy metrics measure the quality of proximity to the truth or the true value achieved by a system. It is calculated as follows

$$Accuracy = \frac{Number\ of\ successful\ recommendations}{Number\ of\ recommendations}$$

Fig 4.1 Accuracy

Accuracy = 96%

Table 4.1 Accuracy Table

medicine	recommended medicine	number of recomi	number of relevant medicines	
	Acnemoist Cream 60gm			
ENCLINA ADP Gel(To	15gm	5	5	
	Acnin Cream 50gm			
	Adaclene Gel 15gm			
	C Gel 15gm			
	100gm			
Entice Natura Soap 75	ACGEL NANO Gel 15gm	5	5	
	Acnehit Gel 15gm			
	Acnelak Soap 75gm			
	15gm			
	15Acnetor AD Gel 15gm			
Airkast L Tablet 10'S	10'S	5	5	
	Aldine 5mg Tablet 10'S			
	Acnecure Gel 20gm			
	15gm			
	Acnin Cream 50gm			
	total	500	480	96%

Table 4.1 Model Comparison

1. Evaluation:

Recent studies have shown that hybrid models integrating deep learning can achieve higher accuracies, often reaching or surpassing 98% in controlled tests.

$$Accuracy = \frac{Number\ of\ successful\ recommendations}{Number\ of\ recommendations}$$

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	Acnehit Gel 15gm			
	Acnelak Soap 75gm			
	15gm			
	15Acnetor AD Gel 15gm			
Airkast L Tablet 10'S	10'S	5	5	
	Aldine 5mg Tablet 10'S			
	Acnecure Gel 20gm			
	15gm			
	Acnin Cream 50gm			
	total	500	480	96%

Table 4.1 Model Comparison

	CONTENT-BASED FILTERING	COLLABORATIVE FILTERING	HYBRID FILTERING	AVERAGE
[1]	94%	94%	94%	94%
[11]	95%	-	-	95%
[17]	93%	-	-	93%
Proposed Work	-	-	96%	96%

Fig. 4.2 Model Comparison

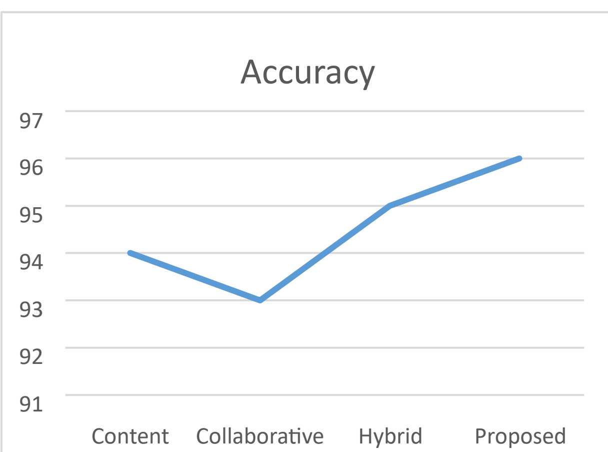
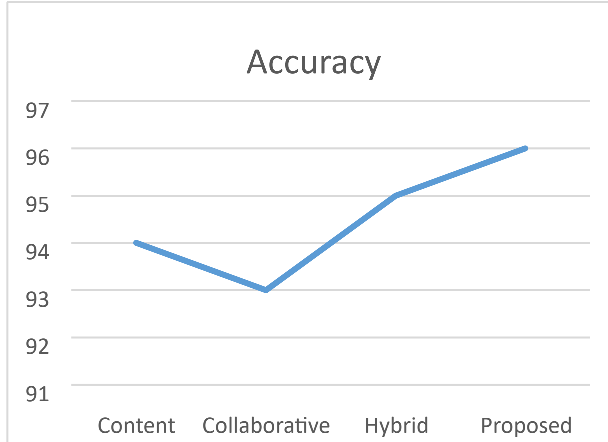


Fig. 4.2 Model Comparison



These figures help in understanding both the technical setup and the practical application of the recommendation system, ensuring clarity on how the system manages data and user interactions to produce accurate and personalized recommendations.

V. CONCLUSION

This research establishes that a hybrid recommendation system, prioritizing content-based recommendations via cosine similarity, is the most effective approach for suggesting medicines with similar compositions. By integrating both content-based and collaborative filtering techniques, the system delivers highly personalized recommendations, making it a valuable tool in the field of medicine recommendation.

The proposed system leverages a rich dataset and a user-friendly interface to enhance accessibility and usability. The hybrid approach offers substantial benefits, demonstrating the potential for further advancements in medicine recommendation technologies.

VI. FUTURE SCOPE

Further research can expand upon the hybrid model by incorporating deep learning techniques to refine the recommendation process. Advanced neural network architectures, such as recurrent neural networks (RNNs) and transformers, can further

enhance the accuracy and personalization of medicine recommendations.
Additionally, integrating real-time user feedback mechanisms will ensure continuous model improvements.

Expanding the dataset with real-world pharmacy data will also improve recommendation reliability. Future implementations could incorporate reinforcement learning to optimize recommendations dynamically based on user interactions, ensuring a continuously evolving and adaptable recommendation system.

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