AetherWell: A Smart Digital Healthcare Solution

Dr M P Pushpalatha[1], Sharadhi N N[2], Shivam Menda[3], Veekshith D[4], Mithali S R[5]

[1]*Professor, Dept. of Computer Science and Engineering, JSSSTU, Karnataka, India.*
[2]*Student, Dept. of Computer Science and Engineering, JSSSTU, Karnataka, India.*
[3]*Student, Dept. of Computer Science and Engineering, JSSSTU, Karnataka, India.*
[4]*Student, Dept. of Computer Science and Engineering, JSSSTU, Karnataka, India.*
[5]*Student, Dept. of Computer Science and Engineering, JSSSTU, Karnataka, India.*

---***---

Abstract - *The healthcare landscape is evolving rapidly, and the demand for intelligent systems that can assist individuals in disease identification and connect them with relevant healthcare professionals is paramount. This paper introduces a cutting-edge health recommendation system that leverages deep learning collaborative filtering, specifically Alternating Least Squares (ALS) to provide individualized recommendations enhancing accuracy and personalization. The system predicts the top ten diseases based on symptoms and also recommends a specialized doctor for each predicted disease, creating a comprehensive healthcare recommendation platform. The proposed solution aims to empower patients and healthcare providers with actionable insights and recommendations related to disease prevention, management, and overall well-being.*

Key Words: **Deep Learning; Collaborative filtering; Health recommendation system;**

1. INTRODUCTION

In an era marked by an abundance of health data and a growing emphasis on personalized healthcare, this paper introduces an innovative health recommendation system. By blending deep learning with collaborative filtering, it aims to revolutionize how people access and utilize health-related information, ultimately striving to enhance overall well-being. This system represents a significant advancement in health recommendation technology, offering tailored guidance for healthier lifestyles and more informed healthcare decisions.

The central challenge addressed is the necessity for an efficient and personalized health recommendation system. Despite the wealth of available health data and information, individuals often find it challenging to make informed choices regarding their well-being. The task involves harnessing deep learning and collaborative filtering methodologies to construct a robust system capable of navigating extensive healthcare data, delivering highly personalized suggestions, and directing individuals towards healthier habits and better-informed healthcare decisions. This system endeavors to tackle this challenge and contribute to the evolution of sophisticated, data-driven solutions in the field of health recommendations, with the potential to shape the future of healthcare guidance and promote a healthier society.

Furthermore, the significance of this research extends beyond individual well-being to broader societal implications. By empowering individuals with personalized health recommendations, the potential exists to alleviate strain on healthcare systems by promoting preventative care and healthier lifestyles. This system not only addresses the immediate need for personalized guidance but also lays the groundwork for a paradigm shift in healthcare delivery. By leveraging advanced technologies such as deep learning and collaborative filtering, opens the door to more efficient and effective healthcare interventions tailored to each individual's unique needs. Ultimately, the implementation of such a system could lead to improved health outcomes on a population scale, fostering a healthier and more resilient society.

2. OBJECTIVES

1) User-Specific Health Recommendation Model

Developing a collaborative filtering-based recommendation model using PySpark to provide personalized health recommendations to users based on their historical health data, preferences, demographics, and behaviors. Using techniques such as matrix factorization, the implemented model takes the user's reported symptoms as input to predict the top ten likely diseases the individual might be experiencing. The objective is to facilitate early disease detection and also significantly reduce the risk of misdiagnosis, ensuring more precise and targeted healthcare interventions.

2) Implementation of an Interactive User Interface

The task involves crafting and executing an intuitive user interface (UI) employing suitable frontend technologies (NextJS), tightly integrated with the backend recommendation system constructed using PySpark. This UI should empower users to input their health-related details, preferences, and symptoms, and subsequently receive personalized health recommendations grounded on predictions generated by the collaborative filtering model.

The goal is to construct a UI that is easy to navigate, responsive, and delivers a smooth user experience.

3) Doctor-Specific Recommendation System

Developing a specialized module within the health recommendation system that offers evidence-based suggestions and treatment plans to healthcare professionals (doctors) based on specific patient diagnoses. Utilizing the collaborative filtering model to analyze aggregate patient data, treatment outcomes, and historical records to generate suggestions for doctors regarding optimal treatment approaches, medication prescriptions, lifestyle modifications, or further diagnostic tests aligned with particular diagnoses. The objective is to incorporate this functionality into the system to assist healthcare providers in making informed decisions and enhancing patient care.

3. PROPOSED SOLUTION

The proposed method introduces a groundbreaking personalized healthcare recommender system that leverages a deep learning collaborative filtering approach using Alternating Least Squares (ALS) for enhanced accuracy and usability. Unlike the existing methods outlined in the two research papers, this novel approach takes a holistic approach by considering user-reported symptoms as input and generating the top ten likely diseases a person might have. Additionally, the system suggests a doctor specifically tailored to address the predicted disease, thereby offering a comprehensive healthcare solution. The objectives of this proposed method are threefold.

Firstly, it aims to create a User-Specific Health Recommendation Model using collaborative filtering and PySpark. By incorporating matrix factorization techniques, the model utilizes historical health data, preferences, demographics, and behaviors to predict potential diseases based on reported symptoms. The goal is to enhance early disease detection and minimize the risk of misdiagnosis, ensuring precise and targeted healthcare recommendations.

Secondly, the proposed method focuses on an Interactive User Interface Implementation, developing a user-friendly interface using React or similar technologies. This interface allows users to input health-related information and symptoms, receiving personalized recommendations seamlessly integrated with the collaborative filtering model's predictions.

Lastly, the proposed method introduces a Doctor-Specific Recommendation System, which provides evidence-based suggestions to healthcare professionals. By analyzing aggregate patient data and treatment outcomes, the system generates recommendations for doctors, including optimal treatment approaches, medication prescriptions, lifestyle modifications, or additional diagnostic tests tailored to specific diagnoses. This functionality aims to empower healthcare providers with informed decision-making tools, thereby enhancing overall patient care.

4. METHODOLOGY

The objective is to develop a collaborative filtering-based recommendation model using PySpark to provide personalised health recommendations to users based on their historical health data, preferences, demographics, and behaviors. The Implemented Model takes the user's reported symptoms as input to predict the top ten likely diseases that the individual might be experiencing. The system not only facilitates early disease detection but also significantly reduces the risk of misdiagnosis, ensuring more precise and targeted healthcare interventions.

1) Data Collection and Preprocessing: The first step in building our Project was to gather the necessary data. This data could include electronic health records (EHRs), patient history, medical literature, and any other relevant health information. Once collected, the data must be pre-processed to ensure it is in a suitable format for analysis.

a) Data Collection: We obtained a diverse dataset containing patient health information, including medical history, symptoms, diagnoses, treatments, and outcomes.

b) Datasets used: We have used a Symptoms dataset with all possible 306 Symptoms, and a Diagnosis Dataset with all the 1537 cures for the symptoms and we have combined these 2 datasets into a matrix of size 5570 Suggestions.

2) Collaborative Filtering with ALS: Collaborative filtering is a widely used recommendation technique. We have implemented the Alternating Least Squares (ALS) algorithm for matrix factorization, which is effective for collaborative filtering.

$$\arg\min_{U,V} \sum_{\{i,j|r_{i,j}\neq 0\}} \left(r_{i,j} - u_i^T v_j\right)^2 + \lambda \left(\sum_i n_{u_i} \|u_i\|^2 + \sum_j n_{v_j} \|v_j\|^2 \right)$$

with λ being the regularization factor, n_{u_i} being the number of items the user i has rated and n_{v_j} being the number of times the item j has been rated. This regularization scheme to avoid overfitting is called weighted-λ-regularization.

Fig 1 – ALS-Matrix Factorization Formulae

a) Data Modeling: We created a user-item interaction matrix based on patient records. The matrix represents user preferences for different health services or recommendations. ALS will factorize this matrix into user and item matrices to capture latent features.

b) Model Training: We split the data into training and validation sets to evaluate the ALS model. We also tuned hyperparameters like rank, regularisation, and iterations to optimize the model's performance. Finally, the ALS model was used to predict missing values in the interaction matrix.

3) Content-Based Filtering: In addition to collaborative filtering, we have employed Content-Based Filtering to enhance recommendation accuracy. This approach involves analyzing the content of the health services or items themselves and matching them with the patient's profile.

a) Feature Engineering: Extract relevant features from the health services or items, such as keywords, descriptions, and medical classifications. Transform these features into numerical representations.

b) K-Nearest Neighbours (KNN): We have implemented the K-Nearest Neighbours algorithm to find similar items based on content features. Calculate item similarities using distance metrics (e.g., cosine similarity). For each patient, recommend items that are similar to the ones they have interacted with based on content.

4*) Evaluation and Testing:* To assess the performance of our health recommender system, we conducted thorough evaluation and testing.

a) Metrics: Evaluate the system using common recommendation metrics Root Mean Squared Error (RMSE).

We have successfully implemented the model which gives us the top 10 recommendations based on severity. We have also achieved **0.87** as the **RMSE score**.

5. ALS MODEL RESULTS

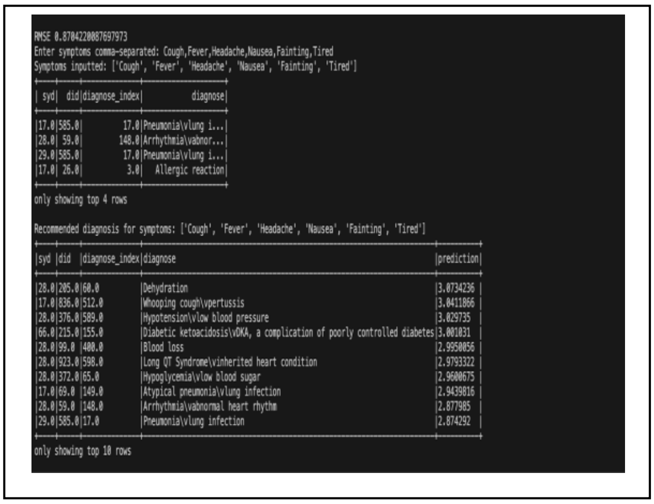

Fig 2 – Disease Recommendation System

In this paper, we employed an ALS (Alternating Least Squares) model to provide personalized recommendations in the domain of healthcare. Leveraging a collaborative filtering approach, our model effectively analyzed patient data and symptom profiles to generate top 10 recommendations for potential diseases. The ALS algorithm, a widely adopted technique in recommendation systems, facilitated the identification of disease patterns and associations based on similarities among patients' symptoms and medical histories. By iteratively optimizing latent factors representing disease and symptom features, the model accurately captured complex relationships within the dataset, resulting in refined recommendations tailored to individual users. Our results demonstrate the effectiveness of the ALS model in providing relevant and personalized healthcare recommendations, offering valuable insights for enhancing patient care and decision-making processes in clinical settings.

6. SYSTEM DESIGN AND FLOW

Our Backend consists of the following collections

a) User and Doctor: Authentication Model

b) Appointments: To track all appointments

c) Doctor Appointments and User Appointments: To track User and Doctor Specific Appointments

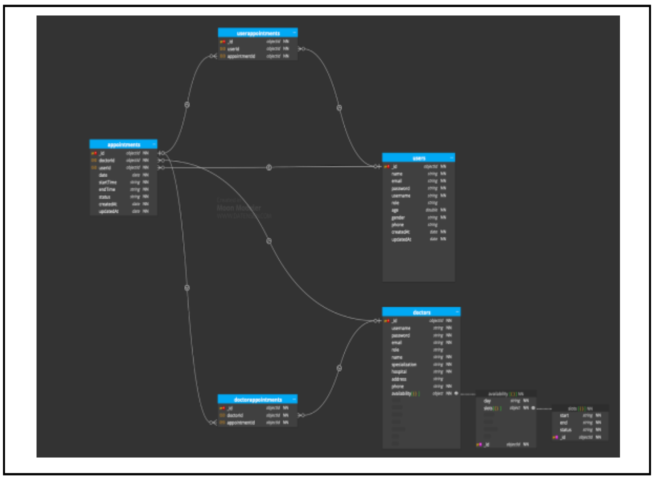

Fig 3 – System Design

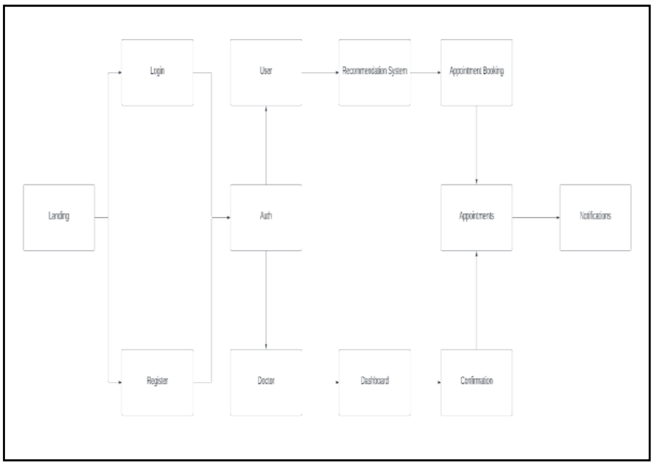

Fig 4 – System Flow

This Schema has been split into a NoSQL database because this helps us maintain Consistency and speed throughout the database. The availability is tracked as part of the doctor model. The appointments are linked both to the users and doctors to track transactions from both ends. The doctor and user appointments are specific to the doctor and the user gets the appointments concerning a specific doctor and user.

Our application has the User and the Doctor's side which have their capabilities and features that help them manage their recommendations and bookings accordingly.

7. SYSTEM IMPLEMENTATION

Through our research endeavors, we have successfully developed a website featuring an integrated system for recommendations and bookings. This platform represents the culmination of extensive theoretical exploration and practical application, with the primary goal of enhancing user experiences in the realms of recommendations and reservations. By harnessing the latest technologies and methodologies, our website delivers personalized recommendations tailored to each user's preferences and needs, thereby facilitating informed decision-making. Moreover, our booking system simplifies the reservation process, providing users with a seamless and efficient means of securing their desired services or products. The meticulous design and thorough testing of our website underscore its effectiveness in addressing real-world challenges within the domains of recommendation systems and online bookings.

8. RESULTS

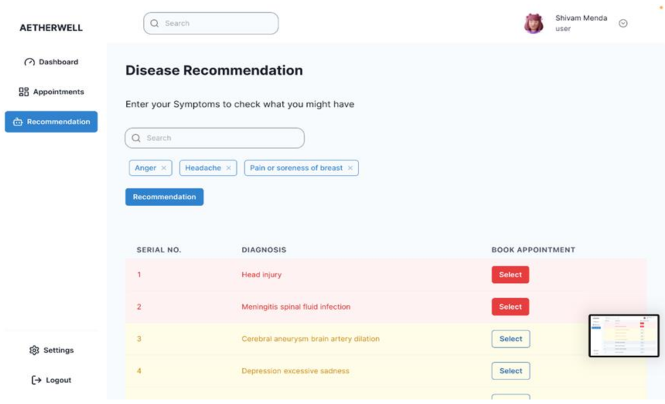

Fig 5 – Disease Recommendation Page

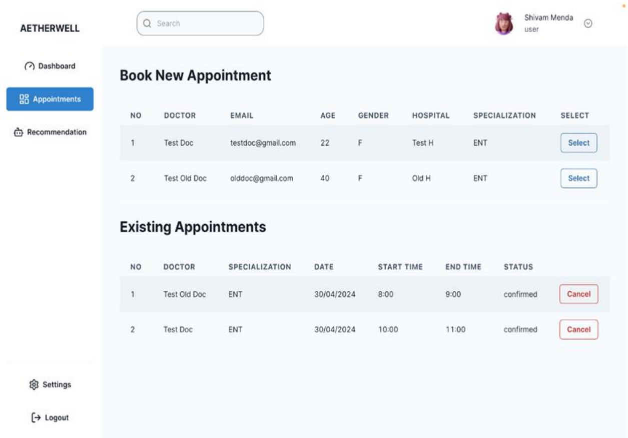

Fig 6 – Appointments Page

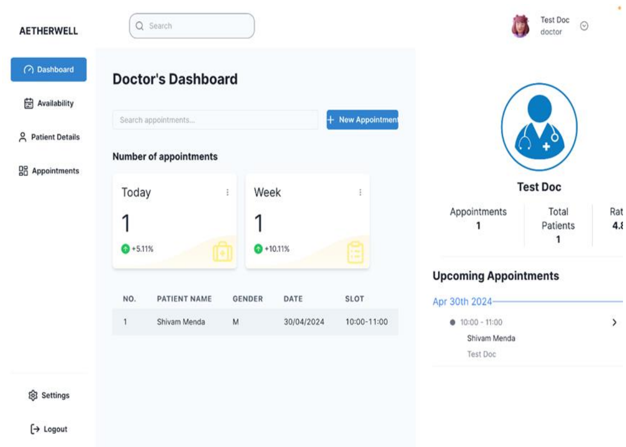

Fig 7 – Doctor's Dashboard

9. CONCLUSIONS

Ultimately, our work represents a significant breakthrough in the field of health recommendation systems. We have created a powerful tool that can provide people with individualized health recommendations and improve their general well-being by combining deep learning and collaborative filtering techniques. By combining these methods, we are able to provide consumers with recommendations that are extremely relevant to their individual requirements and situations by utilizing large archives of health data. This individualized strategy could encourage healthier habits and help make better decisions about healthcare. Our study is proof of the effectiveness of smart, data-driven solutions in meeting this expanding need, as the demand for individualized health recommendations keeps rising. All things considered, our work makes a major addition to this domain and paves the way for future developments in individualized health counseling.

ACKNOWLEDGEMENT

We extend heartfelt gratitude to Dr. M P Pushpalatha for their guidance and support. Thanks to our families, friends, and peers for their unwavering encouragement throughout this research.

REFERENCES

[1] Abhaya Kumar Sahoo, Chittaranjan Pradhan, Rabindra Kumar Barik and Harishchandra Dubey (2019) "DeepReco: Deep Learning Based Health Recommender System Using Collaborative Filtering", Computation 2019, 7(2): 25(2019);

[2] Abdelaaziz Hessane, Ahmed El Youssefi, Yousef Farhaoui, Badraddine Aghoutane, Noureddine Ait Ali, Ayasha Malik (2022) "Healthcare Providers Recommender System Based on Collaborative Filtering Techniques",3(2);

[3] Health Recommender Systems: Systematic Review https://www.ncbi.nlm.nih.gov/pmc/articles/

PMC8278303/

[4] https://spark.apache.org/docs/2.2.0/ml-collaborative-filtering.html.

[5] https://medium.com/radon-dev/als-implicit-collaborative-filtering- 5ed653ba39fe