International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 09 Issue: 07 | July 2022 www.irjet.net p-ISSN: 2395-0072

B-Fit: A Fitness and Health Recommendation System

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Abstract - *In the modern world, health and fitness plays a major role in one's life. People are preferring a healthy lifestyle which can be achieved through regular exercises and a healthy diet. Due to lockdowns and people are staying at home everywhere, people are unable to access workout places like gyms, public parks or even go for a walk. So, ease their problems, our project" B-Fit: A Fitness and Health Recommendation System" aims at bringing access to our users a wide range of fitness videos and personalized content based on the user preferences. Inthe same platform, the user can also access their diet chart based on the height, weight which is used to calculate their BMI (Body Mass Index). Also, healthy food recommendation is also availableto the user by classifying the user as healthy or unhealthy based on their age, weight, height, RBC, WBC, haemoglobin, platelets, sugar etc. in their blood parameters.*

***Key Words*: Fitness, Recommendation, BMI, User Interests, collaborative filtering**

1. INTRODUCTION

The Internet and its associated technologies have become an indispensable tool to search products, services or frequently access information needed in our daily lives, e.g., bookinga hotel, purchasing a new device or consulting the weather forecast. We are presently reported to spend an average 6 hours per day connected to the Internet. Amidst this phenomenon, there is an increasing interest in seeking aid in the Internetto embrace healthier lifestyles, e.g., through the search and sharing of information related to fitness exercises and wellness practices, or via smartphone apps. Although gyms and leisure centers are a common choice for users who desire to adoptor maintain an active lifestyle, they are not always withinthe reach of every person, e.g., owing to financial limitations, busy schedules, frequent traveling, etc. Also predicting the eligible Healthy Food's quality is a challenging task. Using classification algorithms, we can predict if a person is healthy or not using variables like age, weight, hemoglobin, BP, bloodgroup, sugar, platelets, RBC, WBC in the Healthy Food'sdatabase.

Taking advantage of the growing demand for online resources to promote exercising, online workout videos have proliferated in recent years as an alternative means to keep users active from the comfort of home or beyond, with several advantageous characteristics.

The main objective includes:

- Food recommendation based on the user's BMI.

- Video recommendation within the fitness domain to support an active lifestyle.

- Platform for workout video recommendation, which benefits from the Youtube-8M labeled dataset and which has a rich variety of categorized video labels.

- The main objective of this project is a recommendedmodel that extends principles from content-based and collaborative filtering by introducing mechanisms to provide end users with meaningful and diverse workout video recommendations.

- Classifying a user as healthy or unhealthy based on blood test parameters and predicting healthy food based on the factor of the blood test that they are lacking.

The scope of the project is that they are convenient, providing 24/7 access to a wealth of fitness resources from anywhere with an Internet connection. They do not require commitment to work out at an externally imposed day or time. With a careful search and use of the resources available, they provide a wealth of workouts from a diversity of instructors. They are cost-effective and can be undertaken in a more individual and private space

2. LITERATURE SURVEY

[1] Ezin, E., Kim, E., Palomares Carrascosa, I. In their paper "Fitness that fits" proposed a model for workout video recommendation, using the Youtube-8M labelled dataset and its rich variety of categorized video labels, thereby enabling fitness workout video recommendations predicated on the users' preferences and their recent viewing behavior. YouTube provides millions of users with access to a wealth of video resources to support them in practicing their preferred work- outs anywhere and anytime. As a result of classification and supervised machine learning processes on data originating from YouTube videos, Youtube-8M incorporates labels associated to the videos, thereby describing the topic(s) to which they belong, including a number of fitness activity types: this amount of labelled video data has an untangled potential to investigate and enhance existing recommendation approaches on large

volumes of video related to specific domains such as fitness.

[2] Butti Gouthami, Malige Gangappa presented in 'Nutrition Diet Recommendation System Using User's Interest' they discuss nutrition recommendations based on BMI calculations which focuses on daily diet plan and nutrition needs. According to user food preferences and consumption we get suggestions, food nutrition's, deficiencies and tracking historyof his food habits. Content-Based Filtering and Collaborative Filtering methods are used to get users choice of his food recommendation for the daily nutrition with the help of USDAdataset and grocery data. A healthy food pyramid is a combi- nation of plant foods, moderate amount of animal products. Which includes vegetables, grains, fruits, oils and sweets, dairy, meat and beans. Generally, a person remains unaware of major causes behind deficiency or excess of various vital substances, such as calcium, proteins, and vitamins, and how to normalize such substances through a balanced diet. With the advantage of technology, the people can leave a healthier lifestyle. In this project to build a system that will aim to recommend appropriate nutrition intake to its users based on bodymass index (BMI) and grocery data preferences. BMI calculate weight status categories which includes underweight, healthy weight, overweight, obese. Grocery data includes seasonal food, user's interested food, plant foods and animal products. This project will help users' daily diet recommendations alongwith BMI range, healthy food choice, eating behavior, healthproblems, and to change user behavior.

[3] James Davidson, Benjamin lieblad, Junning Liu proposed the YouTube Video Recommendation System. They discuss the video recommendation system in use at YouTube, the world's most popular online video community. The systemrecommends personalized sets of videos to users based ontheir activity on the site. They discuss some of the unique challenges that the system faces and how they address them.In addition, they provide details on the experimentation and evaluation framework used to test and tune new algorithms.

[4] Bernard's , In the survey work of authors conclude that the field of social Recommenders Systems (RS) built on implicit social networks seems particularly promising, propose a social filtering formalism, and with their experiments on music and movie preference datasets, they find that one has to test and try a full repertoire of candidate RS, fine-tune parameters and select the best RS for the performance indicator he/she cares for a Authors study the efficiency of social recommender networks merging the social graph with the co-rating graph and consider several variations by altering the graph topology and edge weights. With experiments on the help dataset, they conclude that social networks can improve the recommendations produced by collaborative filtering algorithms when a user makes more than one connection. In this work, we consider our recommendation system to be a social one as a) it applies to the social network of the users of the application, but also b) it can integrate social graph-based information to enhance the recommendation process. The literature survey performed so far shows that most works employ existing datasets from music or movie rating networks to experimentally evaluate the models or algorithms proposed, but none of them applies the proposed solution to a real-world application.

3. EXISTING METHOD

A recommender system will help us to follow user preferences and requirements and allow us to adjust diet and exercise video recommendation. A similar work is done in 'Fitness that Fits', a prototype platform for workout video recommendation, which relies on Youtube-8M video data describing fitness activities based on a hybrid approach incorporating basic principles from content based and neighborhood based collaborative filtering systems to provide end users fitness video based on their profile. Their approach relies on (a) dataset by filtering the original Youtube-8M labeled video dataset and filtering based on Highly viewed, Fitness-related, Videos having machine-generated annotations of 'Beauty and Fitness' narrowed down to 16 labels, associated with highly viewed and popular types of fitness activities. In this system, they consider user preferences and their watching history to model a recommender system. After gathering this information, a diverse recommendation is made to the user to increase user engagement, that is recommendation of videos that the user might not have seen, and the user might watch. Another existing system is CoCare. It recommends videos about physical activity based on a user profile, his/her context. The main challenge of CoCARE is the small set of videos to be recommended, because the selection of the videos is done manually by health experts. Several health recommender systems have this same problem. Today there are many videos which are available on the Internet related to physical activity. These could not be included in the database of CoCARE; because these do not have enough information to be categorized and profiled. Another existing system that uses user interest to make diet recommendations is one that uses USDA database nutrition factor information for each individual food item. The values needed to calculate BMI (body mass index) must be provided as an input for the final diet recommendations to be calculated. The user's diet recommendation is calculated using the second input, which is based on the food ingested that day. Initially, the deficit nutrition is calculated based on the food consumed for that day, and the input nutrients dataset is sorted based on the BMI value, and the deficit food will be filled from the sorted grocery dataset. Food recommendations are based on the obesity parameter. Dietary recommendations are derived based on obesity.

4. PROPOSED SYSTEM

Extending the existing module by taking the implicit and explicit preferences from the users like ratings given to the videos by a community of users. One of the aims of the proposed system is to provide users with recommended videos that are both relevant (in accordance with their current preferences) and diverse. Diversity in workout recommendations may not only help exploring "new" types of workouts the user might potentially like, but also fosters variety of workouts in such recommendations to prevent an eventual sense of boredom Two sources of user data are taken as an input to model their current preferences: the user profile and the recent user behavior.

4.1 DATASET

We have a dataset of open-source YouTube videos with its id's and 12 different labels for our system. YouTube-8M is a large-scale labeled video dataset which, as of June 2018, consists of over 6 million of YouTube video instances (which add up to 350,000 hours of video), namely video IDs with high-quality annotations generated by machine learning techniques, describing a highly diverse vocabulary of over 3.8K different entities (labels). We remark that despite the considerable volume of real labeled video data available, the proposed model uses a small and synthesized dataset that has been achieved through using YouTube Data API v3 provided by google developers. The food dataset particular to Indian cuisine is still not open source and has to be developed over time with the addition of more users and access to a variety of food information.

4.2 RECOMMENDER SYSTEM

Collaborative Filtering, which is also known as User-User Filtering, is a technique which uses other users to recommend items to the input user. It attempts to find users that have similar preferences and opinions as the input and then recommends items that they have liked to the input. There are several methods of finding similar users (Even some making use of Machine Learning), and the one we will be using here is going to be based on the Pearson Correlation Function. We read the data having video titles and ratings and BMI. The recommendation is based on the likes and ratings of the neighbors or other users. Each user has given multiple ratings for different videos. The process for creating a User Based recommendation system is as follows:

• Select a user with the videos the user has watched

• Based on his rating to videos, find the top X neighbors

• Get the watched video record of the user for each neighbor
• Calculate a similarity score using some formula

• Recommend the items with the highest relevance

To find the similarity of users to input users we are going to compare all users to our specified user and find the one that is most similar. we're going to find out how similar each user is to the input through the Pearson Correlation Coefficient. It is used to measure the strength of a linear association between two variables. The formula for finding this coefficient between sets X and Y with N values can be seen in the image below.

4.3 WHY PEARSON CORRELATION?

Pearson correlation is invariant to scaling, i.e., multiplying all elements by a nonzero constant or adding any constant to all elements. For example, if you have two vectors X and Y, then, Pearson (X, Y) == Pearson (X, 2 * Y + 3). This is an important property in recommendation systems because for example two users might rate two series of items totally different in terms of absolute rates, but they would be similar users (i.e., with similar ideas) with similar rates in various scales.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Fig -1: Pearson Correlation Equation

The values given by the formula vary from r = -1 to r = 1, where 1 form a direct correlation between the two entities (it means a perfect positive correlation) and -1 forms a perfect negative correlation. In our case, a 1 means that the two users have similar tastes while a -1 means the opposite. We use the rating of selected users to all videos this is done by taking the weighted average of the ratings of the movies using the Pearson Correlation as the weight as a part of content-based filtering, we are recommending videos based on the similarity between items that are videos in this case. We calculate the similarity between the videos using the ML algorithm (KNN in our case) and recommending the videos which are most like the target video.

5. DESIGN AND IMPLEMENTATION

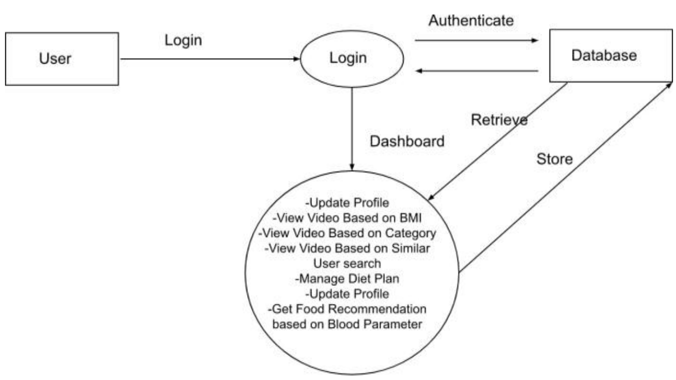

Fig -2: User DFD

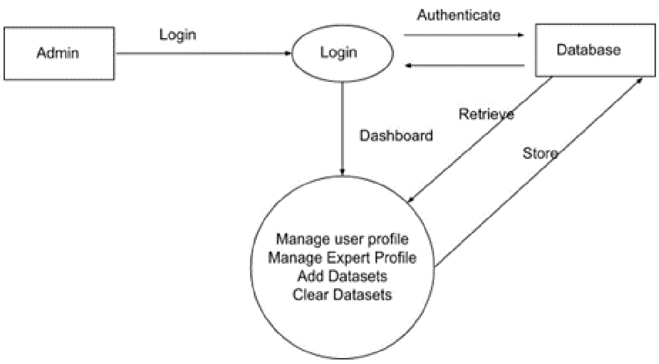

Fig -3: Admin DFD

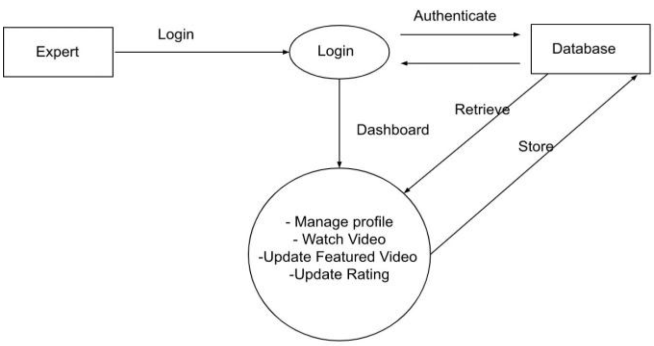

Fig -4: Expert DFD

When it comes to conveying how information data flows through systems (and how that data is transformed in the process), data flow diagrams (DFDs) are the method of choice for the implementation,

- We have used HTML, CSS, JS and Bootstrap for the frontend of the application.

- For the backend, XAMPP server has been used with PHP and MYSQL.

- For the ML model, we have used Python and Anaconda environments with the help of VS code.

Input - User information like Name, Age, Height, Weight etc. Output - Video and diet recommendations based on User information like height, age, weight, gender, preferences etc.

The user enters his/her information in the user profile page and according to that we store the information in the database. Once a user updates the information, based on the BMI calculated, the labeled videos are recommended in one module. Another module is dedicated for the users to rate the videos based on their liking to increase the social capabilities of our project. The rating given by the users will be used as a filter for the collaborative filtering algorithm along with BMI of the users to recommend videos to the users of similar tastes. The users can also view expert recommended videos to help them know if the video is authentic or not. A prototype for food recommendation has also been added and will be further improved with the addition of the diverse dataset. Also, a user can be classified as healthy or unhealthy based on his blood parameters and we are using KNN/Naive Bayes algorithm to classify the user as healthy or unhealthy and then recommend a food diet based on the factor which is classified as unhealthy.

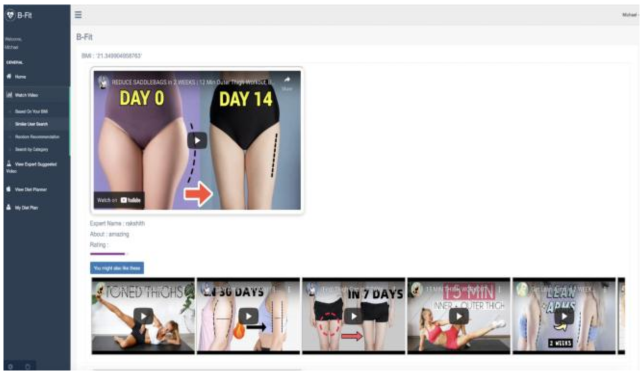

Fig -5: Video recommendation module

The admin module has privileges for the admin which include viewing the users, managing the experts, food and video datasets. The experts are added to rate the videos which are deemed to be authentic in the view of the expert. The expert can rate, add information about the video.

6. TESTING AND RESULTS

6.1 PRECISION

Precision is concerned about how many recommendations are relevant among the provided recommendations.

$$\text{AP@N} = \frac{1}{m}\sum_{k=1}^{N}(P(k) \text{ if } k^{th} \text{ item was relevant}) = \frac{1}{m}\sum_{k=1}^{N} P(k)\cdot rel(k),$$

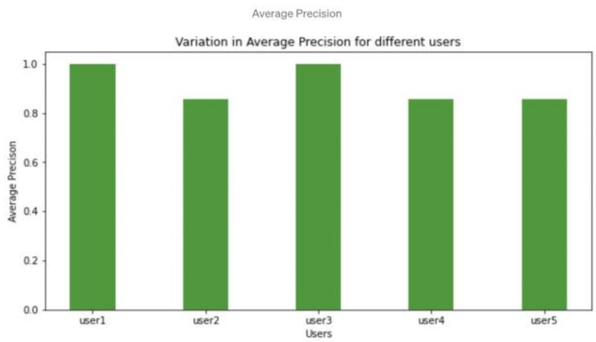

Chart -1: Precision

6.2 RECALL

Recall is concerned about how many recommendations are provided among all the relevant recommendations.

Recall @ k is given by = # of our recommendations that are relevant / # of all the possible relevant items

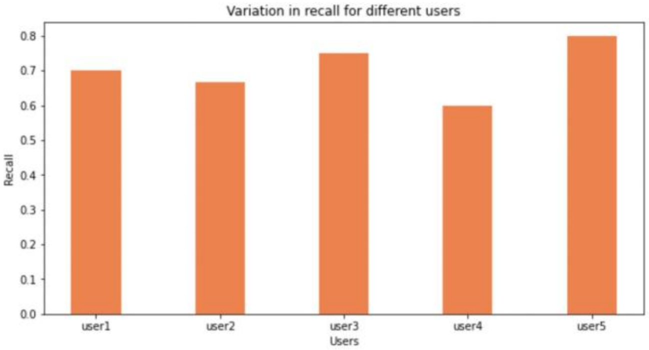

Chart -2: Recall

6.3 AVERAGE PRECISION@K

AP@K is the sum of precision@K for different values of K divided by the total number of relevant items in the top K results.

Precision @ k is given by = # of our recommendations that are relevant / # of items we recommended

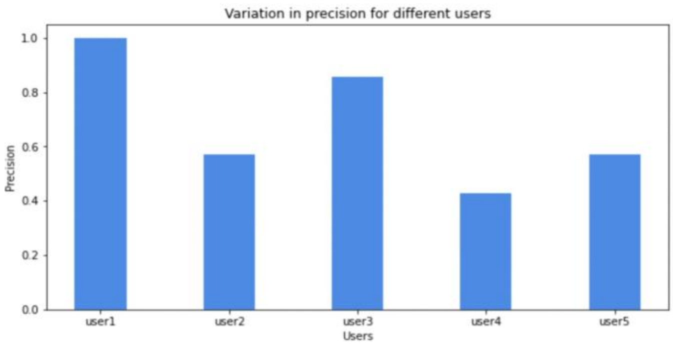

Chart -3: Average precision @ k

6.3 MEAN AVERAGE PRECISION @ K

The mean average precision@K measures the average precision@K averaged over all queries. The mean average precision @K is given by taking the average of AP@K by the total number of recommendations. In our sample case, we got the value as 0.91428 Average precision metric says that the higher the value, the more relevant recommendations have been made.

7. CONCLUSION

B-Fit: A Fitness and Health Recommendation System, aims at bringing access to our users a wide range of fitness videos and personalized content based on the user preferences. Video recommendation within the fitness domain to support an active lifestyle. It is a platform for workout video recommendation, which benefits from the Youtube-8M labeled dataset and which has a rich variety of categorized video labels. The main objective of this project is a recommended model that extends principles from content-based and collaborative filtering by introducing mechanisms to provide end users with meaningful and diverse workout video recommendations. Classifying a user as healthy or unhealthy based on blood test parameters and predicting healthy food based on the factor of the blood test that they are lacking. The scope of the project is that they are convenient, providing 24/7 access to a wealth of fitness resources from anywhere with an Internet connection. They do not require commitment to work out at an externally imposed day or time. With a careful search and use of the resources available, they provide a wealth of workouts from a diversity of instructors. They are cost-effective and can be undertaken in a more individual and private space.

8. FUTURE ENHANCEMENTS

We can provide composite video recommendations by providing smaller videos while providing diversity in recommendations. We can significantly improve the accuracy and diversity of the recommended videos with the availability of more profound datasets for e.g., datasets regarding Indian cuisine. Further enhancement can also be done by introducing advance features such as Activity Tracking, a sensor-based system measuring human movements in terms of calorie, steps taken, cycling activity etc. which helps improve the lifestyle by keeping its users aware about their health.

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