A Comprehensive Research on Hybrid Recommender Systems for Cardiac Patients' Dietary Preferences: Integrating Multiple Algorithms for Enhanced Accuracy

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KEYWORDS
Hybrid Recommender System, Cardiac Patients, Dietary Recommendations, Model-Based Collaborative Filtering, Popularity-Based Algorithm, User-Preference-Based Algorithm, Nutritional Values, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared (R^2) Metrics, Exploratory Data Analysis (EDA), Personalized Nutrition, Machine Learning Algorithms, NBRS Model

ABSTRACT
In this paper, we introduce a new recommender system called NBRS, specifically designed for making food recommendations to people with heart conditions. The NBRS system uses a combination of three different methods: a model that predicts based on what similar users like, a method that considers the most popular choices, and a personalized approach based on individual preferences. We tested the system using nine different techniques—BaselineOnly, CoClustering, KNNBasic, KNNWithMeans, KNNWithZScore, SlopeOne, SVD, SVD++, and Random Forest—to see how well they work in terms of accuracy, using measures like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2).
We gathered a lot of data from both online and in-person sources, focusing on the food preferences and nutritional needs of people with heart conditions. By analyzing this data, we found important patterns that help us understand what kinds of foods are best. The NBRS system significantly improves how accurately it can make recommendations by blending the strengths of these different techniques. This approach is better at suggesting suitable food options for new users, too. Our research shows the value of using several methods together to create a powerful tool for personalized nutrition advice, which could help improve the eating habits and health of people with heart issues.

1 INTRODUCTION

In today's world, where dietary preferences are diverse and ever-changing, food recommendation systems are crucial in helping people find meals that suit their health needs, personal tastes, or cultural backgrounds. Traditional systems often struggle to keep up with these demands, especially for new users who don't have much previous interaction data.
This paper introduces a new hybrid model that combines several techniques: collaborative filtering, which predicts what users might like based on similar past choices; popularity-based algorithms that suggest widely liked items; and new strategies designed to help users without much data. This model aims to make food suggestions more accurate and relevant, addressing the shortcomings of previous systems by adapting to individual preferences effectively and efficiently. This approach not only fills the gaps left by other methods but also enhances the system's ability to cater to a wide range of dietary needs in a personalized way.

2 RESEARCH METHODOLOGY

In this study, we developed a specialized recommendation system called "Nutritional Based Recommendation System" (NBRS) to provide personalized diet advice for heart patients in Gujarat. We began by gathering a large dataset from a popular culinary website, which included over 100,000 user interactions involving ratings and preferences, particularly focusing on Gujarati cuisine. The NBRS uses three key types of algorithms: Collaborative Filtering, which predicts what users might like based on past preferences; Popularity-Based Recommendations, which suggest widely liked items; and New- User Recommendations, designed to help users who are new and have little past interaction data. We rigorously tested the system with standard evaluation metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) to ensure it provides accurate and relevant dietary suggestions.

2.1 Data Collection

In this research, we collected two types of data to develop an accurate food recommendation model for cardiac patients in Gujarat. We focused on both primary and secondary data sources to gather relevant information. This comprehensive data collection helped us create a model that effectively suggests suitable dietary options for these patients.

2.1.1 Primary Data Collection

In our research, we directly collected primary data from cardiac patients to ensure our findings are relevant and precise. We used interviews, surveys, and questionnaires to understand their dietary needs and health status. After obtaining informed consent and securing permission from the Primary Health Center in Subhash Nagar, Porbandar, we were able to gather valuable insights. This thorough approach helps us tailor dietary recommendations to improve patient care effectively.

2.1.1.1 Online & Physical Collection of Cardiac Patients Data

In our research, we collected data from cardiac patients using both online and in-person methods to capture a complete and varied set of information. We utilized Google Forms for online data collection, allowing patients to conveniently provide details about their dietary habits, food preferences, and health status. This method was particularly beneficial for those unable to participate in person due to health or mobility issues. For physical data collection, we interacted directly with patients at the Primary Health Center in Subhash Nagar, Porbandar, where we collected more personalized dietary and health data. We also included a food item rating system in both methods, asking patients to rate their preferences on a scale from 1 to 10. This dual approach helped us gather a rich dataset that accommodates different levels of digital literacy and provides a comprehensive view of each patient's dietary needs and lifestyle, including detailed demographic information and daily activity levels.

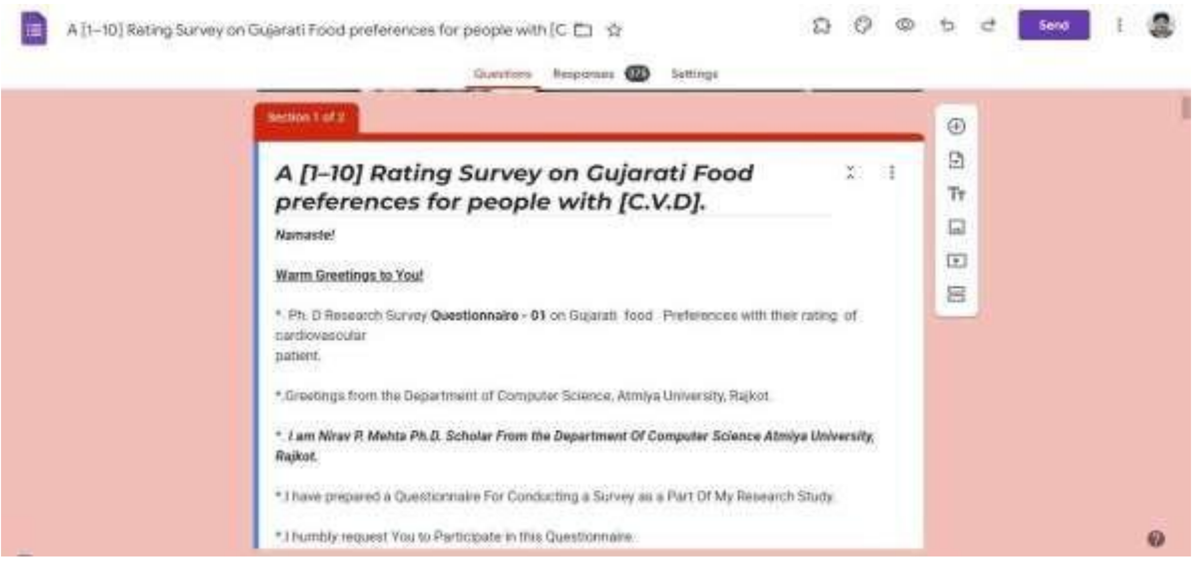


Figure 1Google Form for Cardiac Patient Information

2.1.1.2 Online Collection of Food Preference of Cardiac Patients

To understand the dietary preferences of cardiac patients, we conducted an online survey using Google Forms, targeting participants' food choices, especially within Gujarati cuisine. Patients rated a wide array of food items on a scale from 1 to 10 based on their personal preferences and consumption frequency. The survey, which included about 90 food items distributed across

15 questions, not only captured their preferences but also educated them about the nutritional values of these foods. This approach was beneficial as it allowed participants to complete the survey at their convenience, enhancing the reliability of the data. The results, depicted in various graphs in our report, clearly illustrate the trends in food preferences among cardiac patients, highlighting the most and least favored items and providing critical insights to tailor dietary advice effectively.

Figure 2 Food Preferences of Cardiac Patients with Rating [1 to 10]

2.1.2 Secondary Data Collection

Our research extensively used secondary data to gather detailed nutritional information on various Gujarati food and fruit items. We sourced this data from reliable nutritional databases, scientific studies, and government health resources. This allowed us to compile nutritional profiles for a broad range of dishes and fruits typical in Gujarati cuisine, helping us understand the dietary patterns of cardiac patients better. This crucial information aids in creating specific dietary recommendations to improve patient health outcomes. Additionally, we used graphical representations to clearly illustrate and compare the nutritional content across different foods, making our findings more accessible and understandable.

2.1.2.1 Database for Gujarati Food & Fruit Items Nutritional Values & Calorie Specification

2.1.2.1.1 Gujarati Food

In our study, we focused on the nutritional analysis of traditional Gujarati dishes to offer tailored dietary recommendations for cardiac patients. We closely examined the content of proteins, carbohydrates, fats, fiber, and calories in 14 different categories of Gujarati cuisine. This thorough evaluation ensures that the selected foods are beneficial for heart health and suitable for managing cardiovascular conditions. The nutritional details of these categories, including common main meals, are summarized in a table that highlights the essential nutritional values of each serving, helping to guide personalized diet plans for these patients.

2.1.2.1.1.1 Nutritional Value for Main Meals in Gujarati Cuisine

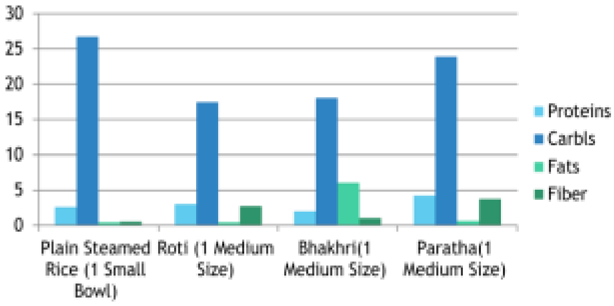


Figure 3 Nutritional Values for Main

Meals 2.1.2.1.1.2Nutritive Values for Dry Snacks in Gujarati Cuisine

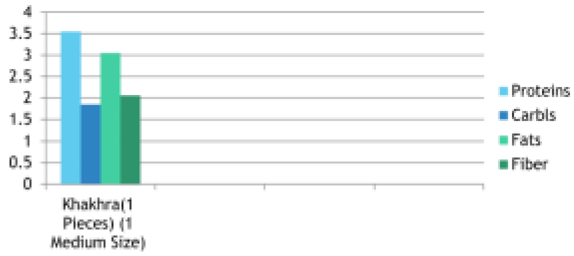


Figure 4 Nutritive Values for Dry Snacks

2.1.2.1.1.3 Nutritive Values for Main Meal Dal & Subji in Gujarati Cuisine

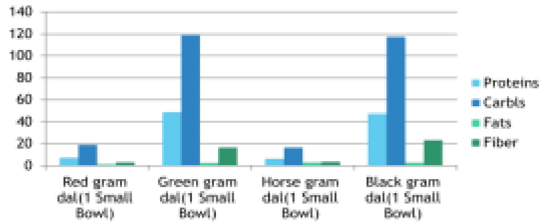


Figure 5 Nutritive Values for Dal & Subji 2.1.2.1.1.4 Nutritive Values for Gujarati Snacks in Gujarati Cuisine

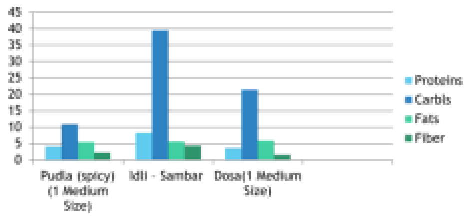


Figure 6 Nutritive Values for Gujarati Snacks 2.1.2.1.1.5 Nutritive Values for Leafy Vegetables in Gujarati Cuisine

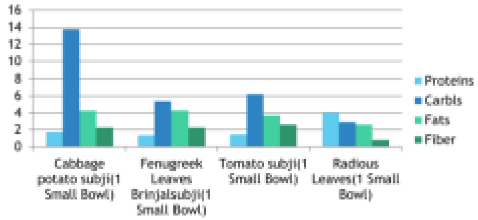


Figure 7 Nutritive Values for Leafy Vegetables

2.1.2.1.1.6 Nutritive Values for Other Vegetables in Gujarati Cuisine

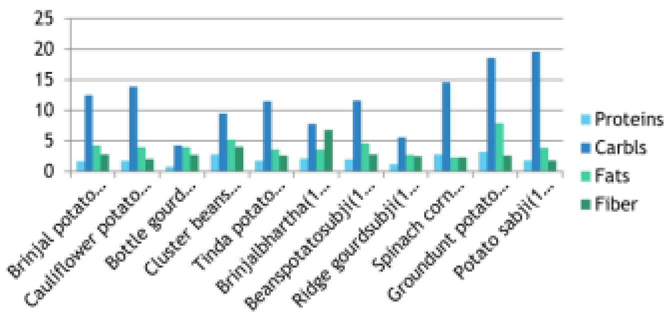


Figure 8 Nutritive Values for Other Vegetables

2.1.2.1.1.7 Nutritive Values for Sambhara(2 Table Spoon) in Gujarati Cuisine

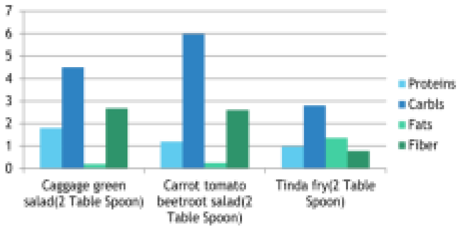
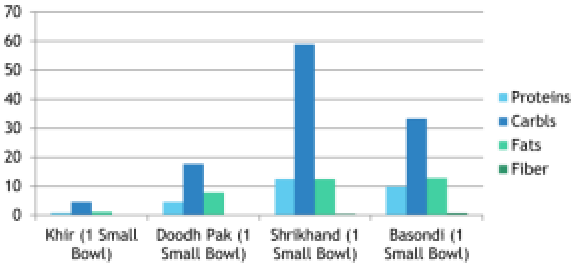


Figure 9 Nutritive Values for Sambhara(2 Table Spoon)

2.1.2.1.1.8 Nutritive Values for (Milk Product) (1 Small Bowl) in Gujarati



Cuisine

Figure 10 Nutritive Values for (Milk Product) (1 Small Bowl)

2.1.2.1.1.9 Nutritive Values for (Cereal + Pulse Product) (1 Small Bowl) in Gujarati Cuisine

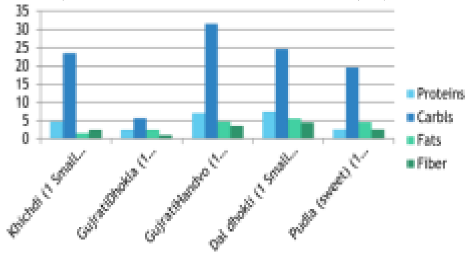
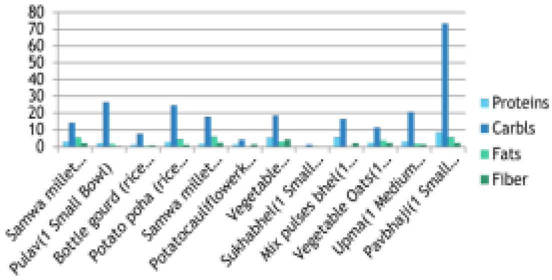


Figure 11 Nutritive Values for (Cereal + Pulse Product) (1 Small Bowl)

2.1.2.1.1.10 Nutritive Values for (Cereal + Vegetable Product) (1 Small Bowl) in Gujarati



Cuisine

Figure 12 Nutritive Values for (Cereal + Vegetable Product) (1 Small Bowl) 2.1.2.1.1.11 Nutritive Values for (Pulse + Vegetable Product) (1 Small Bowl) in Gujarati Cuisine

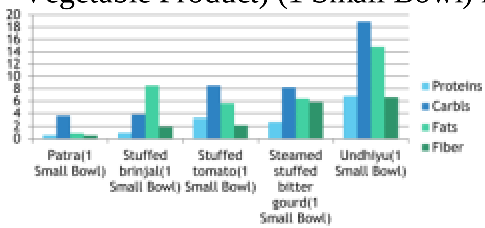


Figure 13 Nutritive Values for (Pulse + Vegetable Product) (1 Small Bowl)

2.1.2.1.1.12 Nutritive Values for (Cereal + Pulse + Vegetable Products) (1 Small Bowl) in Gujarati Cuisine

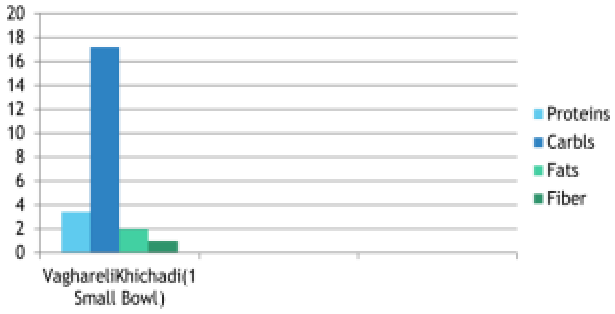


Figure 14 Nutritive Values for (Cereal + Pulse + Vegetable Products) (1 Small Bowl)

2.1.2.1.1.13 Nutritive Values for (Milk + Pulse Product) (1 Small Bowl) in Gujarati Cuisine

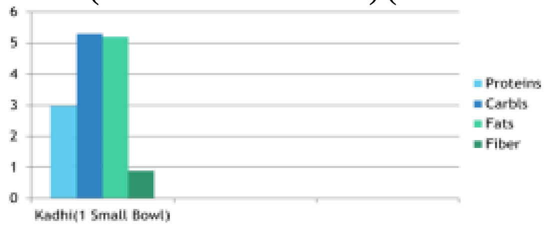


Figure 15 Nutritive Values for (Milk + Pulse Product) (1 Small Bowl) 2.1.2.1.1.14 Nutritive Value for (Oil Seeds Product) (1 Small Piece) in Gujarati Cuisine

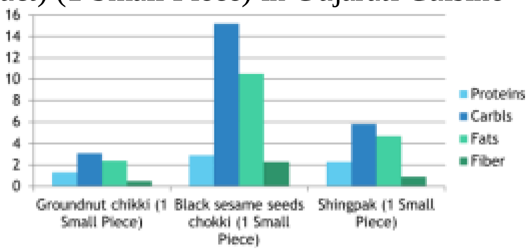


Figure 16 Nutritive Value for (Oil Seeds Product) (1 Small Piece)

2.1.2.1.2 Raw Fruits

Fruits are essential in nutrition studies due to their abundance of vitamins, minerals, antioxidants, and fiber, making them crucial for overall health. They are especially rich in vitamin C, potassium, and dietary fiber, which help prevent chronic diseases like heart disease, diabetes, and certain cancers. Regular fruit consumption can aid digestion, support weight management, and enhance well-being. A table in our study details the nutritional values of various fruits, underlining their importance in a nutritious diet.

2.1.2.1.2.1 Nutritive Value for (Raw Fruits) (1 Medium Size) in Gujarati Cuisine

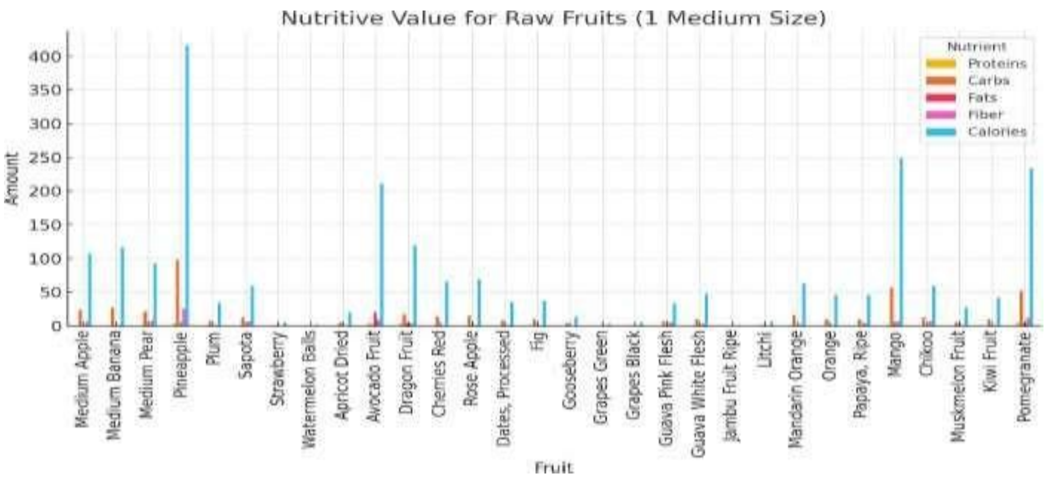


Figure 17 Nutritive Value for (Raw Fruits) (1 Medium Size)

2.1.3 Model Development

In developing the Nutrition-Based Recommendation System (NBRS), the researcher used a hybrid model that combines various machine learning techniques to improve the accuracy of dietary recommendations for cardiac patients. This approach leverages the strengths of different algorithms to analyze user preferences and dietary trends comprehensively. The system was trained using a rich dataset of Gujarati cuisine, incorporating nutritional details and user feedback, which allows for personalized and dynamic dietary suggestions aimed at enhancing cardiac patient health management.

3 RESULTS

In the research presented, various machine learning algorithms were employed within a hybrid model to enhance the accuracy of dietary recommendations for cardiac patients. The performance of these algorithms was evaluated using three key metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2).

MSE and RMSE are critical in assessing the prediction error rates of the models. Lower values of MSE and RMSE indicate higher accuracy in the predictions made by the model, suggesting that the predicted dietary recommendations are closely aligned with the actual preferences and nutritional needs of the patients. For instance, the KNNWithMeans algorithm showed notably low MSE and RMSE scores, implying a high level of precision in its predictions, which is crucial for providing effective dietary guidance.

The R^2 metric, on the other hand, provides insight into the proportion of variance in the dependent variable that is predictable from the independent variables. A higher R^2 value indicates that the model explains a significant portion of the variance, which in this context, translates to a strong ability to predict patient preferences accurately based on the input data. Models like KNNWithMeans and SVDpp(Golagana et al., 2023) exhibited higher R^2 values, highlighting their effectiveness in capturing the complexities and nuances of dietary preferences among cardiac patients.

These metrics collectively help to validate the effectiveness of the proposed Nutritional Based Recommendation System (NBRS), ensuring that it can be reliably used to tailor dietary recommendations that are not only scientifically sound but also closely tailored to the individual health profiles and preferences of cardiac patients. The robust performance across these metrics signifies that the NBRS can significantly enhance dietary management and support better health outcomes for cardiac patients in Gujarat.

The effectiveness of the various machine learning algorithms employed in this research is meticulously documented in the following table, which outlines the results for each algorithm, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) values. This table serves as a comprehensive overview of the comparative performance of each algorithm, providing a clear snapshot of their predictive accuracies. Additionally, the impact and effectiveness of these algorithms are visually represented in the accompanying graphical illustrations. These graphical representations provide a visual comparison of the algorithms' performance, offering an intuitive understanding of their effectiveness in enhancing the dietary recommendations system for cardiac patients. This visual and tabular presentation allows for an easier interpretation of the data, highlighting the strengths and limitations of each algorithm within the research context.

Table 1 Results of Classification Algorithms

Model Name	MSE	RMSE	R^2
BaselineOnly(Wang et al., 2024)	0.725	0.313	0.598
CoClustering(Saifudin & Widiyaningtyas, 2024)	0.357	0.165	0.742
KNNBasic(Ajami & Teimourpour, n.d.)	0.916	0.384	0.602
KNNWithMeans(Tran & Huh, 2023)	0.161	0.077	0.819
KNNWithZScore(Patoulia et al., 2023)	0.198	0.094	0.753
SlopeOne(Muthumali et al., n.d.)	0.198	0.0946	0.782
SVD(Siregar, 2023)	0.286	0.134	0.764
SVDpp(Gupta & Shrinath, 2022)	0.186	0.089	0.798
NMF	4.580	1.340	-0.640

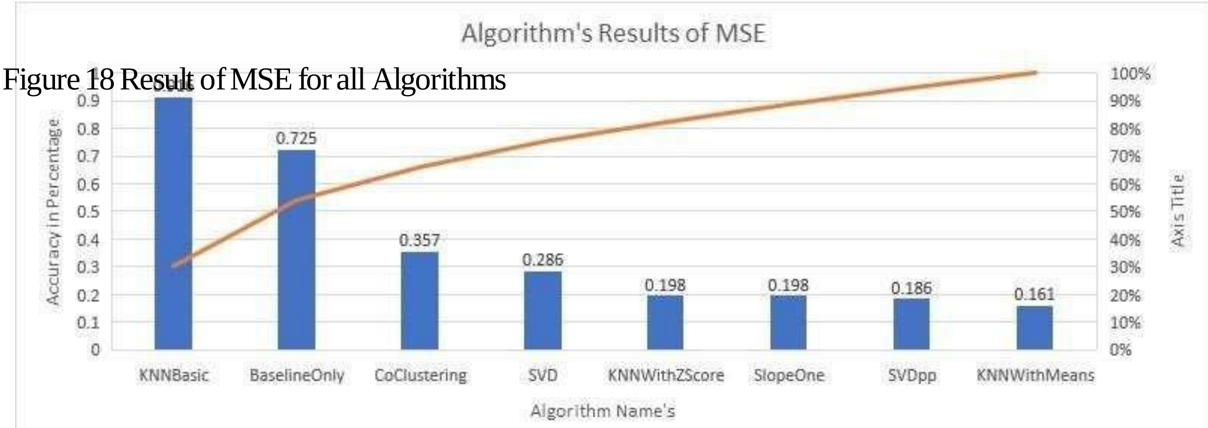


Figure 18 Result of MSE for all Algorithms

Figure 19 Result of RMSE for all Algorithm's

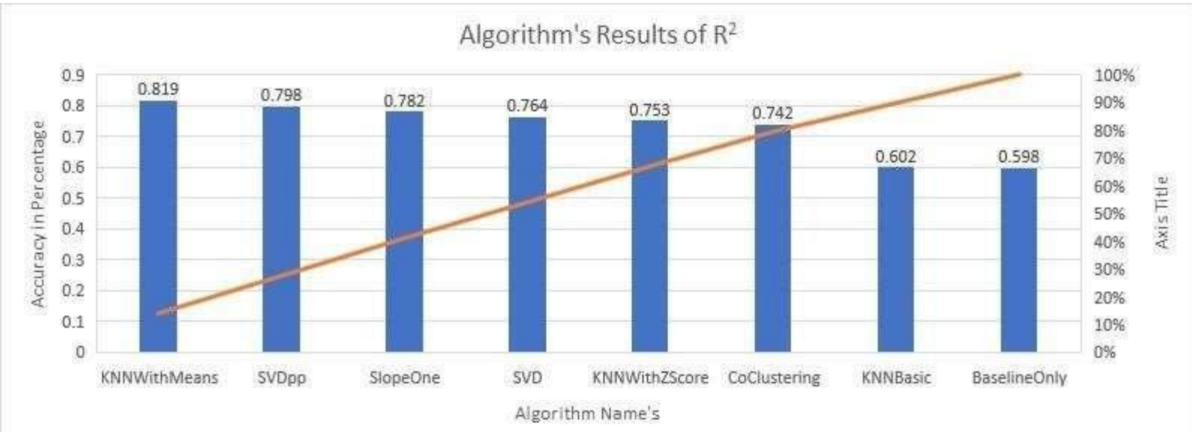


Figure 20 Result of R-Square for all Algorithm's

3.1 Implementation of the NBRS Web Interface:

The implementation of the Nutrition-Based Recommendation System (NBRS) for this research paper involves a detailed explanation of both the code and the interactive web interface provided to the users. Developed using the Django web framework, the NBRS is designed to offer a seamless and intuitive user experience while ensuring robust data processing and secure handling of user inputs.

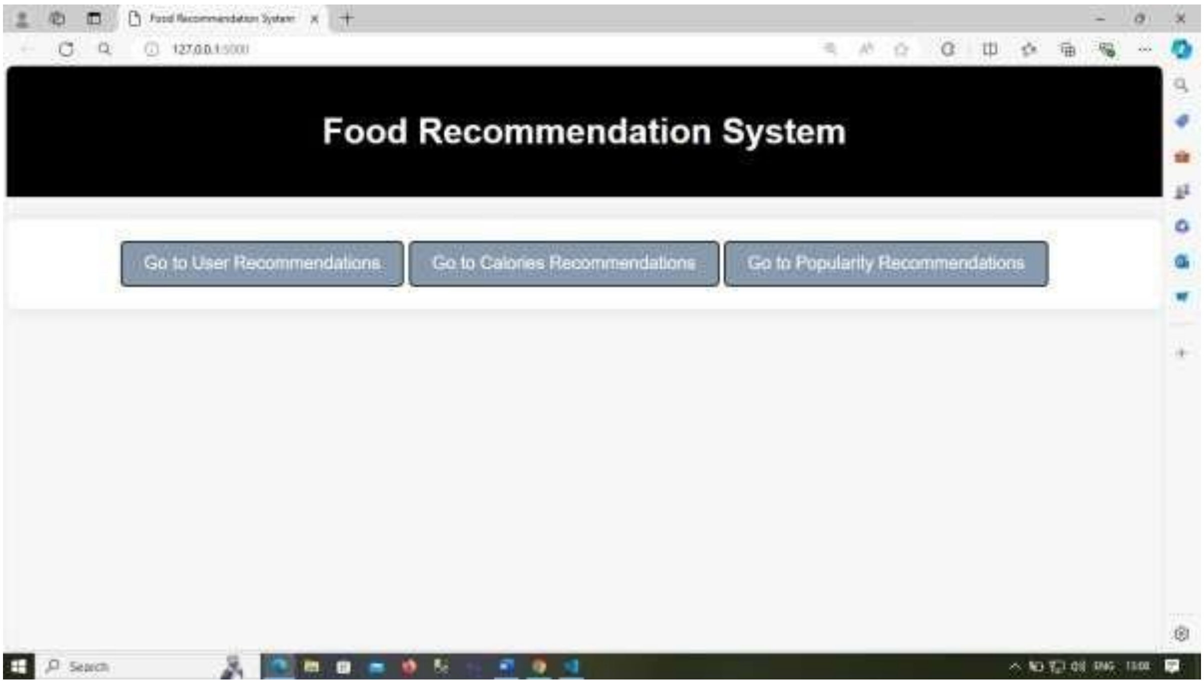
3.1.1 Code Structure and Web Interface:

The web interface of NBRS is constructed through multiple HTML files, each serving a distinct purpose to enhance user interaction and functionality. The primary files include:

3.1.1.1 index.html:

This file acts as the landing page of the system and is crucial for navigation. It provides links to different sections of the system, allowing users to choose from User-Based Recommendations, Caloric Recommendations, and Popularity-Based Recommendations. The design is user-friendly and straightforward, facilitating easy access to various functionalities of the system.

Figure 21 Home Page Food Recommendation System [GUIDesign]



3.1.1.2 user_base.html:

Dedicated to User-Based Recommendations,(Bilgin et al., 2016) this file processes user inputs to generate personalized dietary suggestions based on previous interactions and preferences. It uses forms to capture user details and preferences, which are then processed by the backend algorithms to display tailored food recommendations.

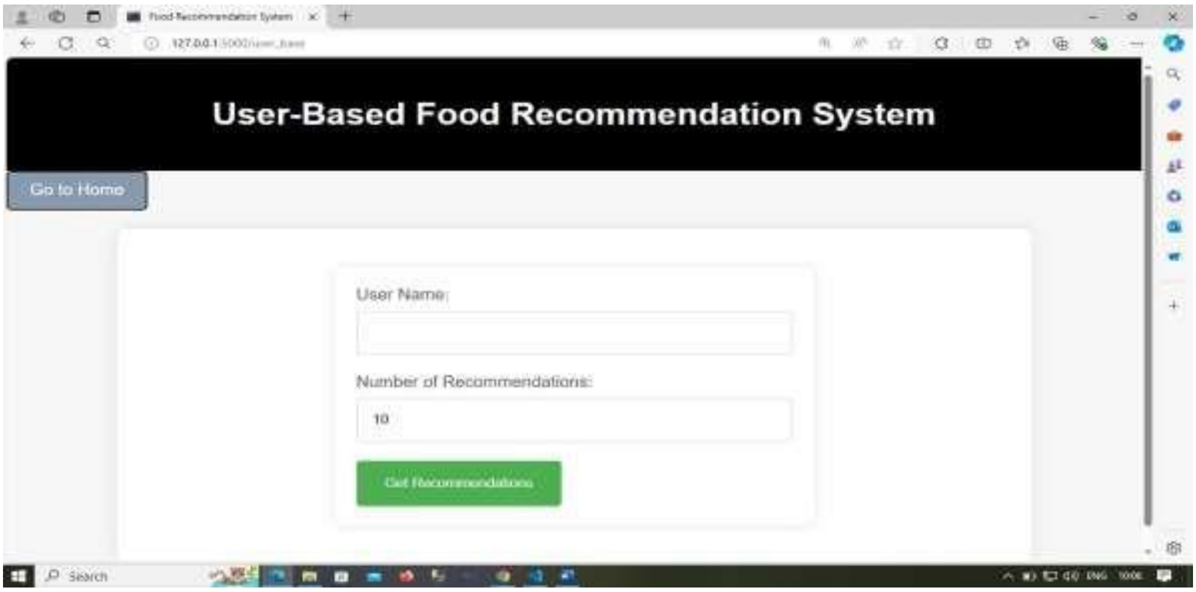


Figure 22 User-Based Food Recommendation System [GUIDesign

3.1.1.3 cal.html:

This file handles Caloric Recommendations by calculating the basal metabolic rate (BMR) and suggesting meal plans that align with the user's caloric needs. It integrates forms where users can input their physical attributes like age, weight, and height, along with activity levels, to receive customized meal suggestions(Chavan & Sambare, 2015) that meet their dietary requirements.

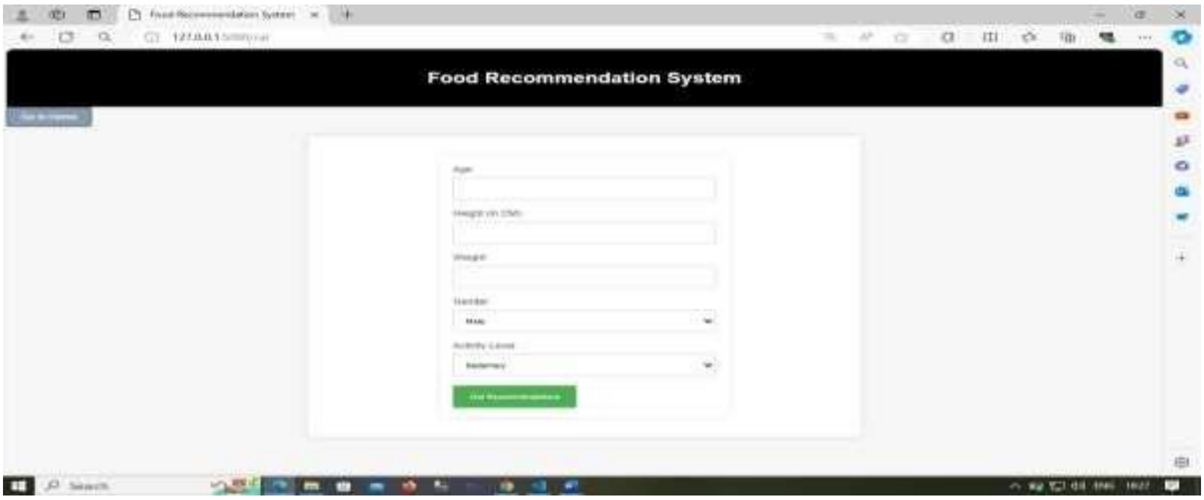


Figure 23 Calories-Based Food Recommendation System [GUI Design]

3.1.1.4 pop_food.html:

Focused on Popularity-Based Recommendations, this file leverages user data to showcase the most popular food items within the community or specific user groups. It helps users discover new dishes that are trending or highly rated by other users, enhancing the communal aspect of the system.

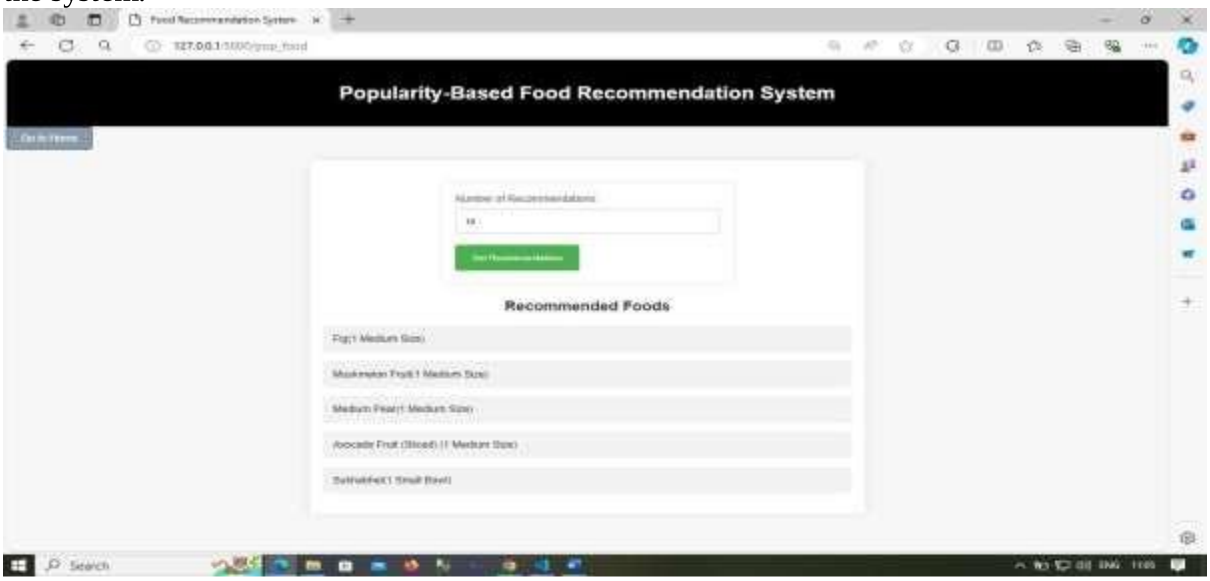


Figure 24 Popularity-Based Food Recommendation System [GUIDesign]

3.2 Functionality and User Interaction:

Each of these files is designed to interact seamlessly with the backend, where complex machine learning algorithms process the data. The Django templates dynamically display the results based on the algorithms' output, ensuring that the recommendations are updated and relevant. Screenshots included in this section illustrate the system's functionality, showing how users navigate through the system, enter their details, and receive recommendations.

The NBRS model's implementation showcases the practical application of theoretical knowledge, blending advanced programming techniques with user-cantered design to create a comprehensive decision support system. This system not only aids in dietary planning but also enhances user engagement by providing a platform that is easy to navigate and responsive to user needs(Yashudas et al., 2024). The detailed code explanation alongside visual proofs of the system's functionality provides a clear picture of how the NBRS operates, making it a valuable tool for cardiac patients looking to manage their diet effectively.

4 CONCLUSION

This paper introduces the Nutritional Based Recommendation System (NBRS), a tool created to improve dietary recommendations for cardiac patients in Gujarat. By using various machine learning techniques, the NBRS effectively personalizes diet suggestions. It supports not only cardiac patient care but also offers potential for wider use in dietary planning and health management. The system's successful application highlights its value in advancing personalized healthcare.

5 FUTURE SCOPE

Looking ahead, there are plans to expand the Nutritional Based Recommendation System (NBRS) to cover a broader range of dietary needs and diverse user groups. Future updates could include adding international food choices to appeal to a global audience. We also want to improve the system by incorporating real-time feedback to constantly adjust and improve the dietary suggestions based on user experiences and health changes. Another exciting direction is to link the system with wearable health devices, which would allow it to monitor bodily responses to recommended diets and offer more tailored and reactive health management.

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