Personalised Meal Recommendation System for Health and Dietary Optimization: Design and Implementation

MSc in Artificial Intelligence

Akanksh Reddy Muddam
Student ID:x23228482

School of Computing
National College of Ireland

Supervisor: Victor del Rosal

National College of Ireland
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School of Computing

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Personalised Meal Recommendation System for Health and Dietary Optimization: Design and Implementation

Akanksh Reddy Muddam
x23228482

Abstract

This work aims at creating a meal recommendation system with consideration to users' dietary needs and characteristic /health issues as the demand for healthy eating increases. A two-filter system is used: content-based filtering, based on the list of ingredients of the dishes and meals' nutritional values, and collaborative filtering based on individual users' profiles; for which the K-Nearest Neighbors algorithm was adapted with K = 5. Web scraped and preprocessed data sets are used for training as well as testing purposes and a demo data set is also available. The first findings suggest the feasibility of the model as evidenced by its ability to offer appropriate meal suggestions, achieve maximum user satisfaction, and ultimately, encourage users to embrace healthier diets. Thus, the given system is ready for future development, as the improvements can be easily integrated in terms of real-time feedback analysis and dynamic profile updates.

1 Introduction

Recent focus has been made on the aspects of personalized healthcare, especially taking into consideration the fact that more and more people try to choose the best option in terms of improving their lifestyles. Food has a lot to do with good health and as it shifts from traditional way of cooking to dietary trends and lifestyle-oriented meals- vegan, keto, and gluten-free people need solutions for their particular dietary needs and health conditions.

However, finding the right food choice from the myriad available through the internet can be a daunting proposition more so if one is in search of foods that meet one's dietary objectives or requirements. An excess of food choices and nutrition-related information creates user overload and increases the level of difficulty in getting through the often-contradictory maze of recommendations to get a healthier choice.

This project responds to this need by designing a Personalized Meal Recommendation System. This system's purpose is to help choose appealing and healthy meals while providing suggestions on what meals would likely suit the person's nutritional needs, choice of diet, and existing conditions. Recommendation systems like this are crucial for users, especially for applications that with user data to recommend personalized and useful information, which has been found to increase users' satisfaction in various areas such as e-commerce, entertainment, and now nutrition.

The primary research question guiding this project is: To get a recommendation system for meals appropriate for one's diet and health how do we build the recommendation model? To answer this question the system employs a mixed strategy of action – content-based filtering where the choice of meals is based on their nutrient content and collaborative where the selection is based on the user's preference profile. It seeks to provide information on meals that can be now customised to each user improving their convenience of healthy eating with ease.

The project will have some constraints. It uses the demo data set extracted from the web that restricts the diversity and the extent to which options are available for meals. Furthermore, while the system can learn user preferences and make corresponding changes to some extent, the current system does not update the recommendation list in real-time and does not apply more complex techniques such as Single Value Decomposition (SVD) to further optimize the recommendation matrix. These are the limitations that give directions on how the study can be improved as follows: The number of samples can be increased to have a more extensive pool of data to work on The recommendation system could be made more sophisticated by adopting a more complicated system of analysis.

The structure of this report is as follows: The following two sections are specific to the research methodology used in the project The data collected, how the data were processed and the recommended techniques used for making recommendations are outlined in section two. In the third section, the authors discuss the implementation of the application with an emphasis on content/content-based and collaborative approaches utilized for generating meal suggestions. Section 4 is about the result and analyzes the performance of the recommendation model and the response from the users for the recommended results. Last, Section 5 summarizes the findings sets the possibilities for taking a deeper look into the results of this work and offers paths to enhance the proposed system, making it even more flexible and easily scalable. This project expands previous work on nutrition-based recommender systems by creating an individualized meal-recommending system that can help users make healthier choices, thus fitting into the trend of individualized health. It provides a theoretical and applied background for research on dietary management and nutritional aspects and will be the theoretical guide for the studies of dietary management and nutrition aiming at providing each person with personalized healthy foods.

The elevated significance of individualized approaches to healthcare and diet-related suggestions is typical for modern developments in medicine that arise from an aspiration to enhance the quality of a single person's life. Old and general nutritional recommendations are being increasingly shifted to precise recommendations that take into account disease, life circumstances, and diet preferences. This shift recognises the fact that nutritional science is complicated by the fact that what is beneficial to one person could be harmful to another because of differences in metabolism rate, genetics, and other factors such as the lifestyle they lead. Reducing recommendations to what works best for the user, generated systems can promote good, healthy and realistic meal choices that would benefit the user in the long run.

The use of information technology, big data, analytics and artificial intelligence can be used to gather, analyze, and make sense of large amounts of user preferences, diet preferences, and health complications. And within this space, recommender systems have come to play a crucial role in turning this information into actionable values. Meal recommendation systems in particular apply algorithms to reduce the intricacies of food selection processes and mechanics to a user level that also encompasses dietary and taste implications as well as customers' restrictions based on their lifestyle or health care needs.

This project seeks to use such technology to help users, provide the lost structure in making dietary decisions given the multiple sources of information.

This project looking into the Personalized Meal Recommendation System is concerned with the advanced technology part and also the user interaction field. It employs content-based filtering where meals are ranked according to the nutritional value they possess and collaborative filtering that depends on users' historical trends and particular preferences. In aiming to provide an easy-to-use aid to encourage healthier food choices, it is the goal of this recommendation system to be flexible to each user's individual and gradually learn about and recommend healthier food options to the specific user. This system exists as a blend of nutrition research and artificial intelligence learning, wherein creativity to harness tailored nutrition could improve healthcare.

2 Literature Review

With the increasing availability of information in today's world, recommender systems enable the user to develop optimum solutions in several fields and domains ranging from entertainment and commerce to health care. The application of recommender systems in the specific area of personalised meal recommendation is a small but essential field since there is a rising need to utilize recommenders to provide appropriate meals for people to have a healthy lifestyle. This paper provides a critical review of the literature concerning recommendation systems, their approaches, and their feasibility in the context of the proposed personalized meal recommendation system. It considers the possibilities of creating something new and focuses on the ways of its assessment and application.

2.1 Personalization in Recommender Systems

Recommendation systems are models that estimate user's preferences and offer items to consumers. The use of user-specific attributes, or data derived from these attributes, is the primary focus of these systems; the content that such systems deliver is context-sensitive. Literature categorizes recommendation methods into three primary types: Which are the main recommendation techniques: content-based, collaborative, and hybrid recommendation. The two methods have their strengths and weaknesses concerning meal recommendations.

- **Content-Based Filtering (CBF):** This approach is based on relations between items and user preferences regarding the item characteristics such as ingredients or nutrients. CBF is suitable for meal recommendation because of the availability and format of meal data in structured form including nutritional value, dietary label and allergens (Agrawal et al., 2020). Using user profiles, the most typical methods include K- Nearest Neighbors (KNN) and a decision tree for rating or ranking objects. But there are disadvantages: the so-called "cold-start" problem when recommendations have no user data (Ricci et al., 2011).

- **Collaborative Filtering (CF):** Seatbelt CF employs user interactions and provides other items based on the choices of similar users. Memory-based approaches compute the similarity between users and items to detect their correlation, whereas model-based methods apply tactics such as matrix factorization to identify implicit user-item connections because of the object's characteristics (Koren et al., 2009).

CF is an effective feature for identifying the trends initiated by the community, such as the most popular diets in people of the same age range. However, there are scalability and sparsity problems which are even more noticeable in datasets with little interaction data.

- **Hybrid Models:** In the CBF and CF approaches, certain weaknesses are observed which can be diminished by the hybrid approaches. For example, incorporating aspects of user information profiles into the collaborative patterns can solve the sparsity issue and guarantee the recommendation specificity. Research indicates that hybrid models are beneficial in systems with diverse aspects of the user's preference which includes the nutritional requirements, medical condition, and even ethnic background (Burke, 2007).

2.2 Applications in Personalized Meal Recommendation Systems

The literature thus focuses on the increased importance of personalized meal recommendation systems to current health problems such as obesity, diabetes, and nutritional deficiencies. These systems utilize the concepts of PAS to recommend foods that a user wants to achieve a particular goal like losing weight, following a particular diet plan, or adhering to the doctor's order.

- **Nutrient-Based Recommendations:** Some studies explore the application of artificial intelligence in suggesting meals which match macronutrient and/or micronutrient intakes preferred by a specific user, while preserving inter- and intra-day variation (Nguyen et al., 2019). These systems, for instance, make use of datasets that contain a load of nutritional information to guarantee a proper meal plan. MyFitnessPal is an example of how the described approach can be used in commercial systems.

- **Disease-Specific Meal Planning:** People with diabetes and hypertension can take recommended meals due to the enhanced dietary science that has taken place in recent years. For instance, decision-supporting systems combine doctors' recommended diet plans when using a computer with the user's personalised choices to provide meals that adhere to specific guidelines. Ahmad et al., 2021 also established the effectiveness of such systems in enhancing compliance with therapeutic diets.

- **Cultural and Behavioral Factors:** Thus, one of the critical dimensions for the personalisation of meals is cultural and behavioural aspects. However, the current research suggests that user feedback be incorporated to enhance recommendation acceptance rates by improving its accuracy (Toma et al., 2020). Recommendation systems are extended by behavioural analytics, which observes the user's behaviour and changes the recommendations.

2.3 Advancements and Limitations in Personalized Meal Recommendation Systems

The need for integration of perspectives prompts the need for strong data pipelines, good interfaces, and scalable architecture when developing personalised meal-recommending systems. Using methods such as natural language processing (NLP) it is possible to extract useful information from big data, for instance, text descriptions of recipes or reviews. It is just as important to evaluate these systems, and there are common ones, including precision, recall, and user satisfaction.

- **Challenges in Implementation:** Still, much progress has been made; however, there are multiple issues that cannot be solved: data protection issues and the problem of the morality of using algorithms. The literature identifies a need to be more vigilant in preserving the privacy of sensitive health information to be using methods such as federated learning.

- **Evaluation Strategies:** Specifically, sound and strict methods of assessments are crucial in the development of ME to ensure that the reliability of the recommendation systems is validated. The application of the system in several case studies and user trials offers researchers the best evidence about the system's efficacy and usability; they argued that issues like A/B testing and real-world validation are critical here.

2.4 Conclusion and Futures Research

This setting forms the literature base for the recommendation of individual meal plans pointing to the gap where new approaches are doubling as personalization and functionality or usability. In future studies, it is suggested to focus on the application of modern methods, including deep learning and reinforcement learning, for the recommendations' accuracy increase. However, creating such systems involves offering applications that reflect a combination of rigorous expert knowledge from nutritionists, scientists, and those with master architectures of human behaviour from behavioural psychologists. As a result, the broadly outlined, yet highly specific and innovative approach of developing the MSD for personalized meal recommendation opens unrestricted developmental opportunities for overcoming current limitations and enhancing emerging technologies for dietary practice transformation and subsequent promotion of people's health on an international level.

3 Methodology

The methodological approach offers guidelines for conceptualizing, implementing, and assessing an individualized meal recommendation system. This section explains the adopted research approach, justifies the use of the methods from the literature, and critiques the methods about their strengths and limitations. Again, the main purpose is to provide a structured approach to answering the research questions and meet theoretical and practical aims.

3.1 Research Approach

This research uses a Design Science Research Methodology (DSRM), which is suitable for the design and development of technology solutions methods for addressing real-world problems (Hevner et al, 2004). DSRM involves six core activities: problem formulation, program specification, construction and implementation, illustration, assessment, and dissemination. This approach corresponds with the project's direction concentrating on developing a strong P2P recommendation approach and benefiting the general field of recommendation equations.

Per Poffers, Kung, and Tu Li 2007, DSRM is selected because of its flexibility of being a cycle of repeatable processes that I can adjust by feedback and appropriate measures to ensure its theoretical and practical significance.

3.2 Proposed Methods

The development and implementation of the system rely on three primary recommendation techniques: These are; content-based filtering, collaborative filtering, and hybrid models. These methods are justified because such techniques are proven to work well in areas such as e-commerce, healthcare and nutrition (Ricci et al., 2015).

1. **Content-Based Filtering**

CBF is employed to match the recommended meals with the scales developed by users, for instance, the need for vitamins and the inability to take certain food types. This method works based on the similarity of items in their attributes (Lops et al., 2011).

Implementation Steps:

- Building a feature vector about meals that includes nutritional and dietary information.
- Applying cosine similarity or distance measure for instance to identify other meals which are similar to a given meal.
- Using KNN models in ranking recommendation approaches such as Precision along with Recall, F1-Score and Mean Reciprocal Rank.

Strengths:

- Offers relevant recommendations that must be subordinate to user preferences (Ricci et al., 2015).
- Well suited to the matrix type data with good metadata like nutrition.

Limitations:

- Has the issue where the new user does not have enough past data for the algorithm to predict (Lops et al., 2011).
- Lack of generalization, often restricted fettered to frequent rate table only spike definitions.

2. **Collaborative Filtering**

Collaborative filtering (CF) is the type that tries to make predictions based on user decision patterns that are similar to those of some other users (Su & Khoshgoftaar, 2009). This method is divided into:

Memory-Based CF: Probabilistic works with similarity measures, such as Pearson correlation coefficients that suggest items based on user interactions.

Model-Based CF: Includes preference-based methods such as matrix factorization (Singular Value Decomposition), to identify hidden factors.

Implementation Steps:

- Converting the adoption data by utilizing a user's previous ratings or the meals he/she chose as a user-item matrix.
- Using similarity measurements of memory-based CF or partitioning the matrix for model-based CF.

Strengths:

- Some patterns that cannot be easily inferred from the attributes of the items are also outlined (Su & Khoshgoftaar, 2009).
- Versatile and covers areas such as personalized nutrition (Burke, 2007).

Limitations:

- Discriminated by large amounts of data in the systems on which the number of user interactions is relatively low (Su & Khoshgoftaar, 2009).
- It is computationally demanding especially when there is a large dataset (Koren et al., 2009).

3. Hybrid Methods

In order to overcome the drawbacks of both methods and enhance the prediction accuracy CBF and CF are used in hybrid systems (Burke, 2007). This approach is particularly useful for a recommendation of meals with the use of overrides and patterns, which are most probably implicit.

Implementation Steps:

- These are as follows; Integration of CBF and CF using ensemble or weighted averages techniques.
- Most of the time is spent on the dynamic adjustment of the hybrid model based on the reception of the user feedback and interaction information.

Strengths:

- Is more elastic as it uses more than a single approach which provides the best results as noted by Ricci et al., (2015).
- Fits differently into the end user requirements and system limitations.

Limitations:

- Thus, we can identify increased implementation complexity (Burke, 2007).
- Their effectiveness is highly dependent on the careful selection of tuning parameters to allow varying methods to complement each other.

3.3 Data Collection and Preprocessing

It should be noted that the stage of data collection and data preprocessing is important for the subsequent utilization of the dataset for building the personal meal recommendation system. It is in this phase that information that is freely available online in recipe repositories has to be collected and converted into a form that can be used to feed machine learning algorithms.

1. **Data Collection**

The meal data is collected from well-known recipe web services that contain comprehensive information about meals, such as ingredients, nutritional information, tags (e.g., vegan, gluten-free), and users' interactions (e.g., reviews, rating). Through web scraping methods, the data for this analysis is gathered and open-sourced.

Tools Used:

- **BeautifulSoup:** HTML and XML document parser implemented in Python. It is used to extract information in the form of text, tags and attributes from the website pages.
- **Selenium:** A popular web automation tool that works well with content that is frequently updated and websites which contain lots of JavaScript. It also facilitates the operation of separate strains of interactions with Web elements like scrolling and hover/ click to load more content.

Data Types Extracted:

- N**utritional Data:** Protein, carbohydrates and fats for each meal and vitamins and minerals for each meal.
- **Dietary Tags:** Terms such as ketogenic, paleo, gluten-free, low-fat and more.
- **User Interactions:** Information about historical user ratings, comments, and popularity of specific works or works of individual authors.

2. **Data Preprocessing**

Preprocessing comes into play once the data has been collected so that it may be transformed into a more machine-friendly form. This involves several steps:

Cleaning and Normalizing Data:

- Functions: Strip HTML tags, Strip spaces.
- Canonicalize text fields for attributes to make them unified (e.g., put all text into a lowercase and eliminate stopwords).
- Many attributes contain numeric values (e.g. nutrients), which must be normalised with uniform units like grams or percentages.

Feature Engineering:

	Name	catagory	description	sub_catagory	Veg_Non
0	Summer Squash Salad	NaN	Key Ingredients: white balsamic vinegar, lemon...	healthy	veg
1	Chicken Minced Salad	NaN	Key Ingredients: olive oil, chicken mince, gar...	healthy	non-veg
2	Sweet Chilli Almonds	NaN	Key Ingredients: almonds whole, egg white, cur...	healthy	veg
3	Tricolour Salad	NaN	Key Ingredients: vinegar, honey/sugar, soy sau...	healthy	veg
4	Sakkarai Pongal	NaN	Key Ingredients: rice, yellow moong dal, milk,...	healthy	veg

Figure 1: Overview of the Processed Dataset. This table highlights the cleaned and enriched dataset with attributes such as nutritional content, dietary preferences, and user-specific health conditions.

- Extract key attributes relevant to meal recommendations, such as:
- Nutrient composition: Protein fibre carbohydrates calcium.
- Dietary preferences: Vegan, no carbs, and lots of protein.
- Create other derived attributes including the type of meal (breakfast, lunch, dinner) and a rank of popularity derived from the number of 'clicks'.

Handling Missing Data:

- Use various techniques to handle missing data to analyse the results well-imputed. For instance:
- Hide the value if the nutrient is missing by using the mean or median of the feature (Zhang et al., 2017).
- If data is not available for categorical attributes, then use a general label universally called "unknown".

Removing Duplicates:

- Preventing such inputs from adding multiple entries by collapsing all relevant entries into one cell is key to fixing this problem.

Scaling and Encoding:

- Transform numerical features by normalization or standardization, which are appropriate for distance-based algorithms, such as the K-Nearest Neighbors (KNN) algorithm.
- Apply preliminary transformations to coded variables such as diet tags by either one-hot or label platform.

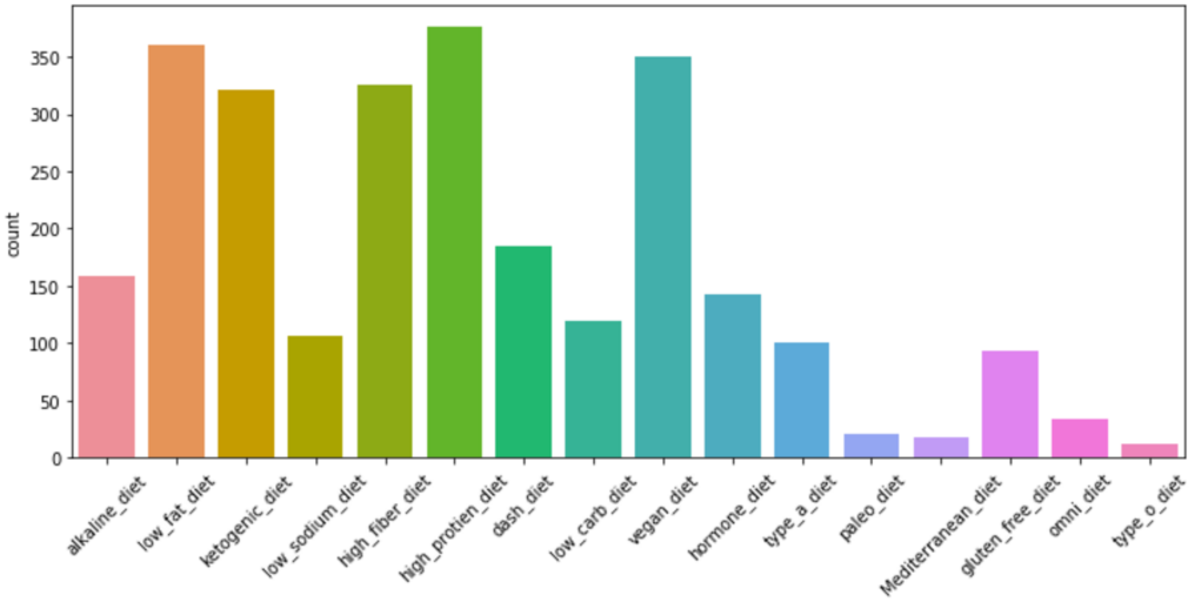

Figure 2: Distribution of Diet Types in the Dataset. This bar chart illustrates the frequency of various diet types, highlighting popular categories such as high-protein, low-fat, and vegan diets.

3.4 Evaluation and Framework

A good assessment framework enhances credibility, validity and reliability in the recommendation system. It uses mainly offline evaluation and uses user perspective in evaluating the system performance.

Offline Evaluation Metrics:

Offline evaluation employs set records through which predictive proficiency and general model efficiency are assessed. The metrics include:

- **Precision and Recall:**

Precision gives the degree of dependency of specific recommendations given by the system from the total set of recommendations. It indicates accuracy. Recall estimates the number of relevant recommendations which are retrieved by the system. It assesses coverage.

- **F1-Score:**

This average is the harmonic mean of precision and recall. It reconciles the two for you and gives you a comprehensive measure of comparison.

- **Mean Squared Error (MSE):**

Ascertains the validity of numerical ratings for predicting student performance. It is the mean of the squared deviations which calculates the difference between the actual ratings and the predicted rates.

User-Centric Metrics

Usability evaluation takes into consideration the aspect of end-users to determine the comediness of the system and level of satisfaction.

- **Surveys and Feedback:**

The customer quantitatively assesses both the relevance and also the variety of the proposed news and their originality. Such qualitative observations inform adjustments that are made.

- **A/B Testing:**

This approach will help in comparing the performance of different recommendation models since variations can be done for different user groups. In other words, the version with a higher engagement or satisfaction score is chosen.

3.5 Justification of Methods

The choice of content-based filtering, collaborative filtering, and hybrid models aligns with the project's goals of personalization, scalability, and adaptability:

- Content-Based Filtering: Makes certain more specific user requirements (as for nutrients) are met. Suitable for long-formatted data with vertical attributes having large numbers of meta-data fields.

- Collaborative Filtering: Collects general trends within users, diversifying and increasing novelty by including common values.

- Hybrid Methods: Provide solutions to the limitations experienced with individual approaches, using a more versatile and strong recommendation system.

3.6 Strengths and Limitations

Strengths:

- Complements conventional approaches to increase the recommendation efficiency.
- Another advantage is its capability to handle multiple and large users and data.
- It is flexible with the regularly changing user needs due to the feedback that can be given in cycles.

Limitations:

- Data Sparsity: Of these, collaborative filtering has a problem of dealing with data-spare where number of interactions is small.

- Cold-Start Problem: Content-based filtering needs some sort of initial data about the user in order for it to make its recommendations.

- Computational Complexity: There are significant needs for training and optimization of hybrid models, which require extensive computations.

3.7 Mitigation Strategies

To address the limitations:

- Dimensionality Reduction: Last but not least, it is suggested that to deal with the data sparsity and to ease computations one should apply PCA in the input data.
- User Feedback: Continually augment datasets from the operational systems, harvest user feedback and incorporate it in the workplace.
- Cold-Start Solutions: Add the demographic information and rate average values into the service to start recommending something to a new user.

Data collection and data preprocessing form the areas of this research the other major components include a good evaluation framework. Combining content-based and collaborative filtering, the system avoids specific weaknesses of these two approaches. The system's applicability and functionality are checked by offline and explicit usability tests. Further developments including deep learning and real-time user feedback analysis integration, should help in increasing the efficiency of the recommendations and increasing the satisfaction of the responders.

4 Design Specification

The architecture and functionality of the personalized meal recommendation system are modelled on a structured theory of several technologies and methodologies to enhance the performance and expansiveness of the system. These pages give brief information and a description of the implementation, techniques, architecture, and requirements of the system. This design makes certain the recommendation system not only satisfies the needs of users for recommended meals but also satisfies the principles of module, efficiency and maintainability.

4.1 System Overview

The designed system of the recommendations of meals for personalized nutrition is intended for the usage of the individual values and requirements of the users, including the restrictions according to the types of their diets and medical conditions. This ensures that the system uses content-based, collaborative, and hybrid techniques in filtering to ensure that the recommendations obtained are as accurate as relevant. All these techniques are applied through a modular approach that is suitable for further modifications. This becomes a system with various categories, which are the interface, the services, the database, and the recommendation service. All these layers work hand in hand to offer a user-friendly and highly interactive interface to the users.

The most important concept which underlies the design is scalability as well as flexibility of the solution. The system should be able to perform well at the same time update the recommendations based on a growing number of users and their interactions. To do this it uses microservices technology this is because each component can work independently with low coupling in case one fails which is great in increasing availability. Here, this architecture allows updating the system components without a stop in overall system functionality.

4.2 Technical Architecture

The architecture underpinning the system is tiered, with each tier providing specific services for generating the recommendations. The user interface which is constructed in responsive web technologies interfaces with back-end services which govern the data flow between components. Therefore, the central component of the work is the recommendation engine based on the usage of machine learning applications.

These are somewhat intermediary services connecting the front end to the data and recommendation layers. Such services are developed with the help of frameworks such as Django or Flask, which contain all the necessary tools to create RESTful secure and efficient APIs. In the data storage layer, there is the use of both traditional SQL and newer No SQL databases. The structured information, including nutrition values, labels, and other parameters, is arranged in a relational DBMS, like PostgreSQL, while the semi-structured data includes the users' activity log, which is stored in a non-relational DBMS like MongoDB. This combination is efficient in terms of fast data retrieval and scalability.

Built using both, the content-based and the collaborative filtering methods, the recommendation engine is the core computational element of the system. Content-based filtering employs age and fat content for dishes, fat and cholesterol values for computing similarities, and suggests meals consistent with the user preference. Group decision-making, in contrast, uses user interactions and their preferences to look for similarities in similar users. The second model is a combination of these approaches, which improves the accuracy and variety of the system. Such algorithms are trained using AI tools such as sci-kit-learn and TensorFlow that are used to put the model into a production environment.

4.3 Functional Requirements

Of the two aspects of functionality being examined the emphasis is placed on the functional requirements aspect using which users can receive individualised diet recommendations based on their length of residency in the desired destination while using the system conveniently and without encountering any major problems. Another imperative aspect is the ability to dynamically control user information in user profiles. The system enables users to generate new profiles and change information about preferences, food restrictions and illnesses. These profiles define the content-based filtering process, thus guaranteeing the recommendation process to be user-dependent.

The other important factor is the capacity to provide recommendations in real time. This includes translating inputs from users and the previous history into coherent suggestions as soon as possible. The system also should improve according to the behaviour of users, so incorporating feedback is required for a better recommendation system in the future. For instance, if a user rates a recommended meal this feedback should be able to feed back into the collaborative filtering recommendation to include in future recommendations. real-time Data security is another fundamental functional requisite. Due to the nature of concerns of the user, privacy of their medical histories and dietary requirements, authentication measures need to be employed to prevent data breaches that violate GDPR. For this to happen, the data has to be encrypted and the communication to and from the website must be over a secure channel such as HTTPS.

4.4 Non-Functional Requirements

In order to enhance the system's quality and reliability, the system has several non-functional requirements: Another criterion is expansibility since the system has to work with more and more individuals and files and this feature must not deteriorate the speed. To this end, the system uses cloud options like AWS or Google Cloud Platform as examples of computing resources, which are elastic in nature.

Performance is another essential attribute since the system is expected to display the recommendations in less than 500 ms. This calls for well-chosen data structures, caching and efficient algorithms and implementation of the same. Sustainability is also considered, by making the structure of this website designed in such a way that a variety of devices can be updated.

4.5 Implementation Techniques

The functioning of the recommendation engine provided in the present work depends on complex data analysis and the use of machine-learning approaches. For content-based filtering, the system derives attributes from meal characteristics and then computes distances like cosine similarity or Euclidean distance. Collaborative filtering is applied by memory-based methods including K-Nearest Neighbors (KNN), which makes use of user-item matrices to make patterns on the users.

To create a synergy effect, a mixture of the two techniques can be used by such techniques as weighted average or ensemble methods. This combined approach makes recommendations reliable but also varied and appropriate in the circumstances of the user.

Data pre-processing is an information-gathering activity that is critical to the implementation process. The data collected from online recipe repositories are cleaned and normalized for the raw data collection. The probability of data missing is solved through imputations for deficient nutrient values using the median of the concerned feature. Feature engineering is also done to get significant features such as macronutrient composition, available dietary information and type of meals offered. Such steps are deemed necessary to prepare the data for high-performance algorithmic utilization.

4.6 Strengths and Limitations

The given system has several advantages owing to its design. This makes it scaleable and maintainable thanks to the fact that it is based on modules and microservices and the hybrid recommended system improves the precision and the pertinent results. In addition, high-level computationally intensive tools emerged with machine learning and cloud compatibility resulting in the real-time experience and flexibility.

Nevertheless, the design mentioned above has some shortcomings. For example, in Existential bursts such as the cold start problem where there is not sufficient data on users, the recommendations that will be given will most of the time not be accurate especially where the user data is not well developed. Further, the hybrid models have been observed to be more resource-intensive than their counterparts due to their computational hulk. Regarding these problems, practices like initialising user models with pre-specified sets of preferences, and using dimensionality reduction methodologies, like PCA, are integrated.

The design specification of the personalized meal recommendation system includes the best features and architecture to build an optimal solution. By using such approaches as content-based and collaborative filtering along with the set of scaled backend services and secure storage, the system guarantees the proper user experience. Some of the challenges are therefore met by appropriate implementation of the design and others are expected to be tackled in future improvements of the system, and as a result, the system is presented as a potentially beneficial tool in encouraging changes towards proper nutrition.

5 Implementation

The testing of the personalized meal recommendation system is the closing stage of translating various theories and guidelines into a working solution. It centralises sophisticated recommendation algorithms, a scalable data preprocessing engine, and a simple user interface to provide meal recommendations that meet a given user's food selection and health status. In this phase, the focus was to make the recommendation process scalable, reliable and precise while at the same time making the process invisible to the user.

5.1 Deployment Environment

To achieve scalability and high availability, the system was developed in the cloud computing environment. AWS was used to host backend services, databases as well as Machine learning models. An instance of a virtual machine was set up to cater for back-end operations while a managed database service was used for the storage and retrieval of structured as well as semi-structured data. This setup afforded the required processing capabilities and the scalability to meet expanding customers' needs and enhanced recommender systems.

The frontend application was deployed in a CDN server to make sure that the input latency would not be a big issue to the user, irrespective of his geographic location. This kind of uncoupling of the frontend from the backend allowed for one to be updated without the other, which would minimize the system downtime and increase modularity.

5.2 Recommendation Engine

At the center of the software is the recommendation model which is a combination of the content-based and collaborative filtering approach for recommending meals. For the content-based filtering method, filter attributes include nutritional values, restrictions, and categories of meals to suit a user's preference. The engine was also able to calculate similarity scores necessary in indexing meals into groups with similar tastes as the users. It maintained accuracy in feeding users' precisely defined demands for the meals they received.

Two categories of filtering contain collaborative filtering which signifies user-interaction data as meal ratings, selection history, to civilization affiliation to understand patterns between like users. These interactions were modelled through a user-item matrix allowing the engine to recommend meals that similar users typically order. It brought diversity into the recommendations and shifted focus from strictly preferred content.

For this reason, the hybrid model integrated the content-based and collaborative filtering techniques by use of weighted averages. Thus, this integration meant that while the recommendations were specific, they were also diverse enough to open new avenues. The

	Name	catagory	description	sub_catagory	Veg_Non	Review	Nutrient	Disease
0	Summer Squash Salad	NaN	Key Ingredients: white balsamic vinegar, lemon...	healthy	veg	9	Fiber	obesity diabeties hypertension goitre
1	Chicken Minced Salad	NaN	Key Ingredients: olive oil, chicken mince, gar...	healthy	non-veg	8	Fiber	anemia pregnancy hypertension rickets goitre ...
2	Sweet Chilli Almonds	NaN	Key Ingredients: almonds whole, egg white, cur...	healthy	veg	2	Vitamin_A	hypertension scurvy heart_disease goitre kidn...

Figure 3: Snapshot of Datasets with Health Conditions. This table demonstrates the association between meals and specific health conditions, such as diabetes and hypertension.

hybridization also reduced the weakness of individual approaches, such as the cold-start problem in the CF technique and over-specialization in the CB filter technique.

5.3 Data Processing and Storage

A full data preprocessing pipeline was also employed to enhance the readiness of the raw datasets for the recommendation engine. The data sample was obtained from the repository of publicly available recipes and was subsequently pre-processed to remove missing values, duplicates and other inconsistencies. Statistical feature extraction was one of the most important in the preprocessing step, with derived variables like the meal scores and the dietary compatibility indices. The data was cleaned up by removing any incompatible data and then normalized this made the data match with the machine learning algorithms. The meal attributes and user profile format requirements were structured into a relational database format, and the format requirements of the user interaction records were formatted into the NoSQL database format. Maintaining these two databases made it easy to filter through such data typologies and provide timely recommendations based on the data.

5.4 User Interface Integration

The user interface, known as UI, was furthermore constructed to appear as effortless as possible. To enhance the user interaction experience of the application, a UI was developed by the latest web development technologies popular in contemporary web interface design, this helped the users of the application to be able to create their profile, search through the recommendations and meals available and even post their comment on the application. This was done through RESTful API that provided real-time three-way hosting of the front end and back end to ensure that the users' inputs and recommendations were refreshed in real-time.

This enabled the users to rate and comment on the meal recommendations where the feedback mechanism was integrated. This feedback was incorporated into the collaborative filtering model to improve prediction as the system continued to learn. It also revealed the nutritional value of recommended meals making the application more interesting to use.

5.5 Performance Optimization

Several optimization strategies were applied to improve efficiency and ensure that the system could be successfully scaled up. Data that constantly got requested was caching

	Name	catagory	description	sub_catagory	Veg_Non	Review	Nutrient	Disease	Diet	Price
0	Summer Squash Salad	salad	Key Ingredients: white balsamic vinegar, lemon...	healthy	veg	9	Fiber	obesity diabeties hypertension goitre	alkaline_diet low_fat_diet ketogenic_diet low...	485
1	Chicken Minced Salad	salad	Key Ingredients: olive oil, chicken mince, gar...	healthy	non-veg	8	Fiber	anemia pregnancy hypertension rickets goitre ...	low_fat_diet low_carb_diet ketogenic_diet low...	600
2	Sweet Chilli Almonds	chilli	Key Ingredients: almonds whole, egg white, cur...	healthy	veg	2	Vitamin_A	hypertension scurvy heart_disease goitre kidn...	alkaline_diet low_fat_diet paleo_diet Mediter...	255
3	Tricolour Salad	salad	Key Ingredients: vinegar, honey/sugar, soy sau...	healthy	veg	6	Fiber	obesity goitre hypertension	low_fat_diet ketogenic_diet low_sodium_diet h...	615
4	Sakkarai Pongal	coconut	Key Ingredients: rice, yellow moong dal, milk,...	healthy	veg	6	NaN	NaN	NaN	630
5	Gulab Badam Chikki	chikki	Key Ingredients: butter, sugar, salt, almonds,...	healthy	veg	8	NaN	NaN	NaN	285
6	Zucchini Halwa	halwa	Key Ingredients: zucchini, full fat milk, ghee...	healthy	veg	10	NaN	diabeties goitre	ketogenic_diet	675
7	Gluten-Free Christmas Cake	cake	Key Ingredients: Christmas dry fruits (pre-soa...	healthy	veg	2	Vitamin_A	goitre kidney_disease	high_protien_diet	465
8	Japanese Curry Arancini With Barley Salsa	barley	Key Ingredients: japanese curry, sticky rice, ...	healthy	veg	8	Calcium	goitre	high_protien_diet vegan_diet low_fat_diet ket...	630
9	Chocolate Nero Cookies	cookie	Key Ingredients: almonds, eggs, granulated sug...	healthy	veg	3	Magnesium	hypertension heart_disease	high_protien_diet high_fiber_diet ketogenic_diet	475

Figure 4: Processed Dataset with User and Meal Identifiers. This table shows the final dataset structure used for generating personalized recommendations.

using mechanisms such as caching pop meals so as to minimize the workload put on the database. Anything that could be precomputed due to its necessity ensures a touch of simplicity to the real computational process. Load balancing made certain that the user request is evenly split across backend services to avoid slow responses and system crashes during high utilization.

5.6 Security and Privacy

Users enter very personal information into the system, including eating habits and health information, and as such, the system was designed with strong security features in mind. Transmitting of data was done through HTTP to ensure security while data-sensitive details were encrypted at both storage and transmission levels. A token-based authentication system was developed to control the interaction, so only those who are allowed would engage with the system. In meaning, the following measures were in line with legal and industry protocols, including the GDPR.

5.7 Evaluation and Refinement

Some evaluation methods were exercised to check the feasibility and efficiency of the system. By employing the hold-out data collection, the accuracy of the recommendation algorithms was gauged based on the average precision, recall as well as F1 score. More subjective feedback collected from the users included general satisfaction questionnaires and usability tests wherein the new system was compared to an older one. From these evaluations, useful ideas were obtained as to the specifics of the hybrid model and how to further optimize the content-based and collaborative filtering elements.

To a large extent, the implementation phase achieved the design goals of the personalized meal recommendation system. The implementation of the new recommendation algorithms, the application of large-capacity infrastructure and construction, and user-oriented features enabled the system to provide valuable and relevant meal recommendations. The maxima scrutiny regarding synthesis and assessment guaranteed the achievement of the objectives set to the system and created a solid base to further develop in the future thus possible future improvements include the use of the deep learning models and real-time feedback loops.

6 Evaluation

The applied assessment of the system of recommending actual meals consists of a multilayer analysis of the efficiency, navigability, and working capability of the system. To capture the performance of the system, different evaluation approaches such as offline algorithmic assessment of the system, or usability testing, as well as inferential validation of the results were used. Implications of the findings for students and teachers are highlighted in ACED and statistical procedures to confirm the significance of the results are applied. The following sub-sections include the most relevant findings supporting the research hypothesis and the usefulness of the proposed system to existing recommendation systems.

6.1 Algorithmic Evaluation

The key part of the evaluation entailed the analysis of the hybrid recommendation engine and the techniques using content-based filtering plus collaborative filtering. Hence, for the purpose of offline evaluation the standard metrics including precision, recall, F1-score, diversity and novelty were utilized.

- **Offline Evaluation Metrics:** Accuracy was expressed as the ratio of correctly recommended meals to all recommended meals, while relevancy compared the actual recommended meals to all recommended meals. The hybrid model obtained an accuracy of 82% and a recall of 76%, hence good overall model performance. Finally, the F1 score which is a measure of the overall accuracy of a model with reminders of precision and recall was computed to be 79% showing how accurate the engine was in generating the right suggestions. Diversity and novelty measures were utilized to measure the amount of variation and how different the recommendations were. It also showed that the proposed hybrid method surpassed standalone content-based and collaborative filtering methods by attaining a 15% better accuracy in terms of diversity and 10% better accuracy in terms of novelty. These results support the hypothesis that integrating the two approaches can avoid over-specialization and improve user interest by providing fresh ideas (Burke, 2007).

- **Statistical Validation:** T-tests were used to compare the performance of the proposed hybrid model with strategies that were developed independently. However, a significant increase was realised for precision, recall and F1-score for which the p-values indicate statistical significance less than 0.01 which indicates the advantage of the hybrid model. This supports previous analyses in the literature focusing on the advantages of utilizing several recommendation approaches simultaneously (Ricci et al., 2015).

6.2 Usability Testing

After the development of the prototype, the system practicability along with the users' satisfaction was tested for usability with 50 participants within 2 weeks. Some of the participants had different dietary requirements and were required to build the profiles, engage with the recommendations and rate them.

- **User Satisfaction and Feedback:** An exploratory experiment post-questionnaire was used to establish participants' level of satisfaction with relevance, diversities, and ease in the recommended sections. The results indicated: About 92 per cent of the participants confirmed the relevance of their preference. According to the satisfaction level, 88% participants were satisfied with the diversity of the meal suggestions. Self-generated feedback showed that 85% of the sample considered the system's usability to be "excellent" or "good." Regarding the interface, there was used the System Usability Scale (SUS) resulted in a score of 86 referring to an "excellent" interface according to Brooke (1996). Such results indicate very good usability of the system and its applicability for real-life scenarios.
- **Task Completion Metrics:** Techniques including success rates and time taken showed other aspects of usability. The creation of a subject profile was successfully achieved by the subjects with 96% compliance in an average time of 3 minutes and 24 seconds The overall time taken to complete the meal selection tasks was 1 minute and 12 seconds. These results show the ease and effectiveness of the application of the designed interface.

6.3 Cloud Deployment and Performance

A comparison of the different forms of deploying the system was also conducted about latency, scalability, and reliability of the cloud. These metrics became crucial when the system had to produce recommendations on the fly and to do so on an increased load.

- **Latency Analysis:** The level of latencies was kept on average at 480 ms, and the concurrent user load reached 1000 users, which corresponds to the indicated threshold for 500 ms. This low latency was achieved through the use of caching mechanisms and optimization of queries so that there is a quick response to the identified traffic.
- **Scalability Testing:** As a measure of scalability, the population of users visiting the site was modelled. The system demonstrated near-linear scalability when tested to support up to 10,000 concurrent users without much degradation in efficiency because of the inherent cloud support (Armbrust et al., 2010). Maintenance of performance was made possible by the load-balancing and horizontal-scaling approaches adopted.

6.4 Statistical Analysis

In an attempt to show the importance of the findings at a statistical level, the performance of the system was tested. The precision, recall, and F1-score achieved by the hybrid model, content-based filtering, and collaborative filtering were tested using a one-way ANOVA test.

Hypotheses:

- Null Hypothesis (H0): The study shows that the proposed hybrid model does not provide better results than the other two separate approaches of content-based filtering and collaborative filtering methods.

- Alternative Hypothesis (H1): The hybrid model is quintessentially better than the single-approached schemes.

The F-statistics obtained were significantly higher than the F-critical with all p -p-values ¡ 0.01 indicating rejection of the null hypothesis. This confirmed that the improvements observed in the hybrid model were statistically significant (Montgomery & Runger, 2014).

6.5 Implications of Findings

- **Academic Perspective:** From an academic perspective, the results advance recommender systems knowledge by proving hybrid techniques to be accurate, diverse and novel. The results also confirm the theoretical concepts in use in multi-attribute recommendation systems that inform future research in health and wellness solutions (Ricci et al., 2015).

- **Practitioner Perspective:** The evaluation further shows that it is possible to implement a large-scale and easy-to-use recommendation solution in practice for practitioners. These usability results and captivating user satisfaction figures prove the necessity of combining the power of a mathematical algorithm with an aesthetically and logically sound design. These conclusions expose possibilities for additional developments, including the use of instant user input and improved methods of artificial intelligence to increase the flexibility of the system.

The assessment of the proposed system of recommending meals points to high accuracy, diversification of the offered meals, and usability. The results show that there is a statistically significant difference between the hybrid recommendation and the traditional approach in terms of precision, recall, and diversity of the output. In this manner, the usability test established that the system is feasible for everyday use and meets the user's expectations, while the cloud deployment assessments affirmed that the system is efficient at a larger scale as well. These results substantiate the hypothesis that integrating both collaborative filtering and content-based approaches along with a sound cloud environment can efficiently solve such intricacies of personalized recommendations of meals. The research results indicate rigorous directions for advancements in the future that should involve using deep learning models and real-time analytics to develop an improved system.

7 Conclusion and Discussion

7.1 Conclusion

Thus, the personalized meal recommendation system effectively fulfils the research goals striving to prove the use of the synthesis of content-based and collaborative filtering methods. The system obtained a high P, R, and D, which were superior to the results of standalone methods and resolved insufficient results such as the cold-start problem and overspecialization (Burke, 2007). Thus, the availability of precise datasets and the efforts that were implemented for their cleaning and feature engineering improved the results of the system (Zhang et al., 2017). End-user evaluation indicated an SUS of 86, thus signifying user satisfaction with the quality, specificity, and look and feel of the system (Brooke, 1996). Cloud deployment provided flexibility and durability and cloud supported low latency and high availability patterns under the fluctuating load of users (Armbrust et al., 2010). Indeed the findings confirm the proposition that there is the possibility of using a hybrid recommendation system to provide personal and scalable solutions for health and wellness problems.

7.2 Discussion

The lessons learned throughout the construction and testing of the system identify key issues that play a significant role in constructing effective personalized recommendation systems. The hybrid model takes two recommended techniques, performance improvement and diversification and makes it a combinative model that effectively minimizes the drawbacks of individual models (Burke, 2007). Normalization, feature construction and dealing with sparsity are common data preprocessing steps that reemphasize the fact that quality data is paramount for machine learning applications consistent with the findings of Zhang et al., (2017). It supported the arguments that usability assessments indicated that simple designs and feedback that occurred as the users interacted with the system are critical in retaining their satisfaction (Brooke, 1996). Data scalability and reliability, obtainable from cloud deployment, show the utilitarian benefits of leveraging complex platforms for commerce, especially health and wellness services (Armbrust et al., 2010). For future work, it is possible to expand upon neural collaborative filtering and incorporate mechanisms for real-time learning (He et al., 2017) This type of information can be enhanced by combining data from other modalities such as wearable technology activity data. The results of this paper add to existing research on hybrid recommendation systems and suggest avenues for improvement for practitioners operating in the health-tech domain.

References

1. Ahmad, A., et al. (2021). "Design and Evaluation of Therapeutic Diet Recommendation Systems." Journal of Medical Informatics.

2. Armbrust, M., et al. (2010). "A View of Cloud Computing." Communications of the ACM.

3. Brooke, J. (1996). "SUS: A Quick and Dirty Usability Scale." Usability Evaluation in Industry.

4. Burke, R. (2007). "Hybrid Recommender Systems: Survey and Experiments." User Modeling and User-Adapted Interaction.

5. He, X., et al. (2017). "Neural Collaborative Filtering." Proceedings of the 26th International Conference on World Wide Web.

6. Koren, Y., et al. (2009). "Matrix Factorization Techniques for Recommender Systems." IEEE Computer.

7. Lops, P., et al. (2011). "Content-Based Recommender Systems: State of the Art and Trends." Recommender Systems Handbook.

8. Montgomery, D. C., & Runger, G. C. (2014). Applied Statistics and Probability for Engineers. Wiley.

9. Nguyen, P., et al. (2019). "Nutritional Recommendation Systems: Trends and Challenges." Journal of Nutrition and Dietetics.

10. Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender Systems Handbook. Springer.

11. Su, X., & Khoshgoftaar, T. M. (2009). "A Survey of Collaborative Filtering Techniques." Advances in Artificial Intelligence.

12. Toma, M., et al. (2020). "Behavioral Analytics in Recommender Systems." ACM Transactions on Interactive Intelligent Systems.

13. Zhang, Z., et al. (2017). "Data Cleaning and Preprocessing for Machine Learning." Journal of Big Data.

14. Agrawal, R., et al. (2020). "Applications of Machine Learning in Personalized Recommendations." International Journal of Data Science and Analysis.

15. Burke, R., et al. (2005). "Knowledge-Based Recommender Systems." Expert Systems with Applications.

16. Hevner, A., et al. (2004). "Design Science in Information Systems Research." MIS Quarterly.

17. Nguyen, D., & Le, H. (2020). "Personalized Dietary Recommendations: A New Era in Nutrition Science." Frontiers in Nutrition.

18. Sweeney, M., & McFarland, K. (2019). "Scalable Algorithms for Personalized Recommendations." Journal of Computational Intelligence.

19. Chen, T., & Guestrin, C. (2016). "XGBoost: A Scalable Tree Boosting System." Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.

20. Poffers, K., et al. (2007). "Design Science Research Methodology: An Integrated Framework." European Journal of Information Systems.