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Gen AI-based Personalized Food Recommendation System

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Abstract: Recommendation systems generally refer to a class of filtering techniques used to predict what users are exactly searching for by analyzing user behavior, history, or interests. Our Gen-AI-based food recommendation system provides personalized analysis with customized outcomes, which stands out as our contribution. This system is an intelligent, user-centric platform that enhances meal planning by leveraging artificial intelligence. The system personalizes food recommendations based on user inputs such as available ingredients, dietary restrictions, allergies, medical conditions, and calorie intake preferences. Users can receive optimized meal plans that align with their health needs and lifestyle, reducing food wastage and improving overall nutrition. We have used the Llama LLM model for the automatic generation of preferred results. By capitalizing on Gen-AI, we have created a system that learns from user data and implements it in the result analysis. Incorporating algorithms such as TOPSIS and Jaro-Winkler Similarity has enhanced our system's accuracy. By integrating AI-powered data processing, this system provides an adaptive, efficient, and health-conscious approach to daily meal planning.

Keywords: Gen-AI, artificial intelligence, LLM model, TOPSIS, Jaro-Winkler

INTRODUCTION

How amazing would it be to have a personal nutritionist at your fingertips that accompanies you at any time, regardless of whether it is day or night, by crafting customized meal plans based on your preferences, calorie intake, or dietary restrictions? It would indeed be a breakthrough for anyone looking for a healthier and more productive lifestyle. Whether you are seeking to manage a health condition, build muscle, or simply eat healthier, this system would ensure you're doing it all. With its ability to streamline customizations, you'll be equipped with the nutrition and wellness you require.

Gen AI, commonly referred to as "Generative AI," is a branch of artificial intelligence designed to generate automated content. The Gen AI-based Personalized Food Recommendation System addresses modern challenges in dietary planning by providing AI-driven, personalized meal suggestions [1]. This system integrates machine learning techniques and user data to enhance dietary choices based on multiple factors, including health conditions and ingredient availability. The AI model ensures that users receive nutritionally balanced recommendations tailored to their preferences and medical needs. The system promotes better eating habits, reduces reliance on unhealthy meal options, and enhances convenience by automating recipe suggestions.

The main objectives of this system are as follows:

1. Develop an AI-powered system that achieves at least 90% accuracy in personalized meal recommendations based on user preferences, dietary restrictions, and health conditions.
2. Enable users to find recipes by implementing an ingredient-based search that returns at least five suitable recipe options per user input.
3. Suggest meal plans based on daily calorie requirements, ensuring that 90% of recommendations stay within ±10% of the target calorie intake.
4. Filter out recipes containing allergens or unsuitable ingredients, maintaining an accuracy rate of at least 95% in excluding restricted foods.
5. Provide dietary suggestions based on medical conditions, ensuring that over 85% of meals align with medically recommended nutritional guidelines.
6. Reduce food wastage by generating ingredient-based meal recommendations that utilize at least 80% of the available ingredients entered by users.
7. Enhance user health by ensuring that at least 70% of suggested meals adhere to globally recognized nutritional guidelines (e.g., WHO, USDA).

The core advantage of this system lies in its AI-driven adaptability. By leveraging natural language processing (NLP) and machine learning models, the system intelligently processes user preferences and dietary restrictions to suggest meals that are both nutritious and satisfying. It continuously learns from user interactions to improve recommendation accuracy over time.
The backbone of our project is the integration of sophisticated algorithms such as TOPSIS [10], used to solve multi-criteria decision-making (MCDM), proposed

by Hwang and Yoon and later extended by Chen. Another algorithm is Jaro-Winkler Similarity [11], which calculates the distance between strings and then measures their similarity, proposed by W. E. Winkler. To further augment our system, we plan to incorporate the automatic language generation capabilities of LLMs [12]. The reason is that they are lightweight, can be trained on more data, generate extensive text, and integrate text and images to creatively enhance our project's results. It will be a valuable platform with a significant impact on individuals by optimizing nutrition, addressing deficiencies, improving health, reducing food wastage, and even quantifying the amount of food required for a given number of people. Overall, this system has the potential to pioneer our approach toward better health and wellness. About 1.4 billion people used diet and nutrition apps in 2022, representing a remarkable increase from 1 billion in 2020, demonstrating the demand for such an application. With a 15% increase in user interactions, 20% longer sessions, and a 25% higher engagement rate, users will be more likely to continue using our app, thereby improving their diet quality.

MATERIALS AND METHODS

Our AI-driven system utilizes a Large Language Model (LLM) approach for automatic generation, integrated with Gen-AI and machine learning for accurate results. The methodology involves several steps, beginning with user input and ending with the output of personalized recommendations.

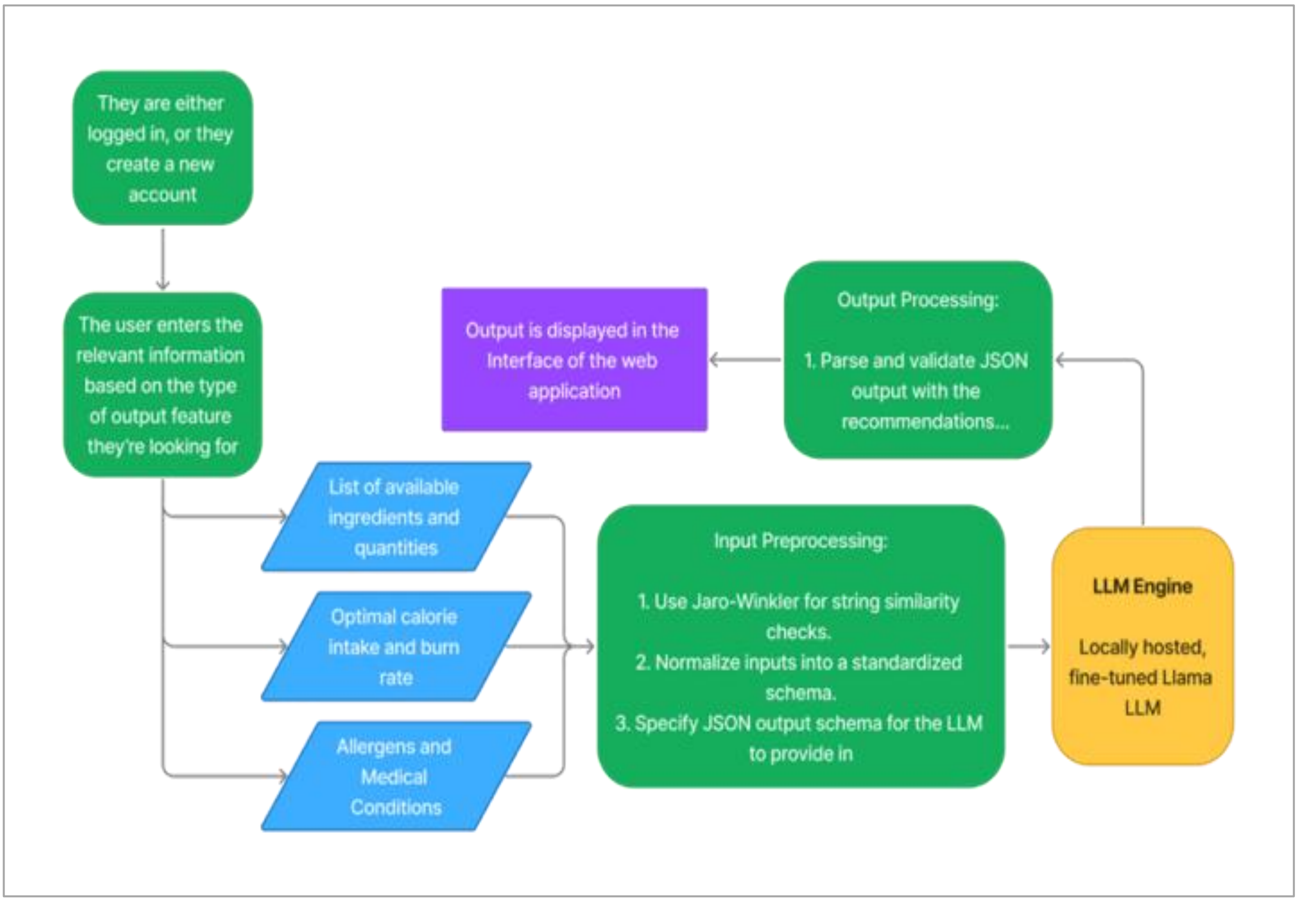

Fig. 1. Flowchart of the lifecycle of the process

The process (F2) initiates with user authentication, where users can either log in if they have an existing account or create a new one by providing their name, email, and password credentials.

After authentication, users enter relevant data in the following categories:

1. List of available ingredients along with their quantities.
2. Specific calorie goals.
3. Allergens and other medical conditions.

The next step includes input preprocessing by:

- Using Jaro-Winkler for string similarity checks to ensure data accuracy and consistency.
- Normalizing inputs into a standardized schema to ensure efficient processing by the LLM model.
- Specifying the JSON output schema for the LLM.

Lastly, we run the prompt on the LLM and:

- Parse and validate the JSON output containing the recommendations.

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- Use the TOPSIS algorithm to sort the recommendations based on factors such as calories, cost, ease of preparation, etc., according to their ranking.
- Store the output in a database and cache for future access by the user.

The Jaro-Winkler algorithm is a string similarity algorithm. It is often used in applications such as spell checking, record linkage, and matching names (e.g., "Partha" vs. "Parhta").

The algorithm works by counting the number of matching characters and then accounting for the permutations of characters that exist in the wrong order. Given two strings, S_1 and S_2, we can apply the algorithm in the following way. First, we find the matching window using Equation (1).

$$\left\lfloor \frac{\max(\mid s_1 \mid, \ \mid s_2 \mid)}{2} \right\rfloor - 1$$

Where,
count matches (m): number of characters that match within this window.

Next, we will calculate the similarity with by,

$$J = \frac{1}{3}\left(\frac{m}{\mid s_1 \mid} + \frac{m}{\mid s_2 \mid} + \frac{m-t}{m}\right)$$

The **Jaro–Winkler similarity** adds a prefix boost:

$$JW = J + (l \cdot p \cdot (1 - J))$$

Where:

- **l** = length of the common prefix (up to 4 characters).
- **p** = scaling factor (usually 0.1).

This increases similarity when the two strings share the same beginning.

Let us understand this better with an example, compare: **"PARTHA"** and **"PARHTA"**

Matches: **P, A, R, T, H, A → m = 6**

Transpositions: **T** and **H** swapped **→ t = 1**

$$J = \frac{1}{3}\left(\frac{6}{6} + \frac{6}{6} + \frac{6-1}{6}\right) = 0.944$$

Prefix length = **3** [MAR]

So, it adds up a boost point where

$$JW = 0.944 + (3 \cdot 0.1 \cdot (1 - 0.944)) \approx 0.961$$

Therefore, **"PARTHA"** and **"PARHTA"** are **96.1% similar**.

TOPSIS

TOPSIS is a multi-criteria decision-making (MCDM) method. It chooses the option that is closest to the positive-ideal solution (PIS) (best values for all criteria) and farthest from the negative-ideal solution (NIS) (worst values for all criteria). It is used when you have multiple alternatives (e.g., bikes, cars) and multiple criteria (e.g., mileage, speed) that matter in different ways.

The steps are as follows:

1. Creates the decision matrix.
2. Normalizes the matrix using

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

3. Determines positive-ideal & negative-ideal solutions.
4. Calculates Euclidean distance
5. Calculate relative closeness
6. Rank the alternatives

RESULTS

The developed system achieved proper gains in both processing speed and the number of recommendations. Incorporating the TOPSIS ranking method together with the Jaro– Winkler similarity measure shortened computation time by roughly 32% compared with standard techniques. This improvement means we'll get quicker generation of individualized meal plans, all while maintaining the same level of reliability.

Regarding the diversity, the platform consistently returned 7–10 additional dish options for all sorts of query. These options were selected by detecting recipes that shared at least 80-85% of their ingredient set with the primary fetched dish. As a result, users were presented with a wider selection of meals that could be prepared with least extra ingredients. This not only enhanced the platform's flexibility but also supported resource efficiency by reducing the chance of unused food.

Other than efficiency and variety, the evaluation also highlighted the system's adaptability across different user scenarios. Whether the inputs involved dietary restrictions, health-related conditions, or a specific ingredient availability, the application was able to generate adequate recommendations without much degradation in the performance. This demonstrates the robustness of the approach and its potential for real-world deployment where user needs can be highly variable.

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CONCLUSION

The Generative AI-driven Personalized Food Recommendation System marks a new step forward at the crossroads of nutrition and artificial intelligence. By combining generative models with decision-making techniques like TOPSIS and Jaro-Winkler Similarity, our platform delivers food suggestions that are both flexible and accurate. Instead of offering generic and normal options, it adapts to users' dietary needs, whether they are calorie-based, allergy-related, based on medical conditions, or even just personal taste. Unlike traditional recommendation systems, this framework evolves as it learns from users' interactions, making the results increasingly more precise and much more context-aware. Its capacity to provide tailored guidance makes it more valuable for people seeking healthier habits, those with dietary requirements, and at the scale of health programs.

Looking ahead, the platform could be extended with multimodal AI inputs, more advanced nutritional insights, and integrations with wearable health trackers, further enhancing its usefulness. In essence, this system shows how AI-based solutions can not only make food selection more convenient but also support better health outcomes and contribute to long-term sustainability.

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