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An Optimized Framework for Personalized Meal Planning using MCDM and the Honey Badger Algorithm

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***Abstract*— This project introduces a personalized meal planner system that uses dietary preferences to intelligently create meal plans that are optimized. Fundamentally, the system uses a Multi-Criteria Decision Making (MCDM) method to assess meals based on user-specified priorities and weighted nutritional components: protein, carbs, and fat. To enable consistent scoring across different magnitudes, nutrient values are normalized using the MinMaxScaler technique. The meals are ranked using a weighted scoring model according to user preferences. The system uses a customized version of the Honey Badger Optimization (HBO) algorithm, a swarm intelligence-based meta-heuristic that mimics honey badger foraging behavior to maximize the overall nutrient satisfaction score, to determine the best meal combination. The model's ability to match meal recommendations with user nutritional goals is demonstrated by its 90% prediction and recommendation accuracy. The complete solution is provided by an interactive web application that was created with Streamlit and features an easy-to-use interface that lets users customize inputs like diet type, preferred cuisine, and nutrient importance.**

***Index Terms*— Streamlit Interface, Honey Badger Optimization, Meal Planning, MCDM, Nutrient Scoring, and Web Application Diet Recommendation.**

I. INTRODUCTION

The need for individualized dietary solutions has increased dramatically in recent years as people look for meal plans that are tailored to their specific needs in order to maximize nutrition for a range of health objectives. Conventional meal planning techniques frequently overlook dietary needs, food variety, and personal preferences. In order to solve this, we suggest a Personalized Meal Planner system that creates customized meal plans by fusing Honey Badger Optimization (HBO) with Multi-Criteria Decision Making (MCDM). Based on their dietary objectives, users can modify the relative importance of protein, carbs, and fat. The system then uses MCDM to rank and assess meals appropriately. To ensure the optimal choice that maximizes the overall nutrient score, the system iteratively refines meal combinations using HBO, an optimization technique inspired by swarm intelligence. A fitness function ranks the meals according to their macro-nutrient content while taking user-specified preferences into account.

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Meal plans that combine MCDM and optimization techniques are guaranteed to be individualized and nutritionally balanced, providing both variety and the best possible distribution of nutrients. An easy-to-use web application built on Streamlit provides this solution, allowing users to enter their dietary requirements, preferred cuisines, and nutrient priorities. Real-time meal recommendations are generated by the system, offering a user-centered, adaptable solution for individualized diet planning. The application provides an effective and adaptable tool that is simple to incorporate into platforms related to health and wellness by combining MCDM with meta-heuristic optimization.

II. LITERATURE SURVEY

- Ahmad et al. (2023) proposed a hybrid Collaborative Filtering and Content-Based Filtering approach for dietary recommendation systems, focusing on user preferences, dietary habits, and food attributes. Their model addresses common challenges such as the cold-start problem and data sparsity, aiming to improve meal recommendations for new users. However, issues like computational complexity still impact the efficiency of their approach.
- Ribeiro et al. (2022) introduced a multi-objective optimization model combined with heuristic functions and a greedy search algorithm to optimize meal recommendations based on nutritional requirements and dietary restrictions. While the approach effectively personalized meal plans, it struggled with the high dependency on dataset diversity and the potential for nutritional deviation when suggesting a limited number of meals.
- Arevalillo-Herráez et al. (2022) used Transformer-based classification with pre-trained embeddings to classify and recommend diets based on tokenized text inputs. Their model leveraged sentiment datasets, but challenges such as computational cost for processing long texts and task-specific performance variations hindered its scalability and general application for dietary recommendations.
- Ahmad et al. (2022) applied Agile Development to build a hybrid filtering system, analyzing user behavior data and dietary preferences. Their model faced challenges related to bias in recommendations and concerns about scalability, highlighting the importance of high-quality user data for ensuring accurate and reliable meal recommendations.
- Rostami et al. (2022) utilized CNN and K-Means algorithms along with community detection methods to recommend meals based on food images and community trends. Although promising, their approach was computationally intensive and required high- quality food images, limiting its applicability in systems with limited image datasets or computational resources.
- [6] Ahmadian et al. (2022) introduced a time-aware community detection approach integrated with reliability measurement and collaborative filtering for personalized food recommendations. Their model used user ratings, nutritional components, and time- based similarity scores to enhance the relevance and accuracy of meal suggestions.

III. METHODOLOGY

Intelligent dietary planning systems are becoming more and more in demand as a result of the exponential growth in health-conscious behavior and the rise in personalized nutrition. Traditional meal planning tools frequently use limited rule-based logic or static templates, which make it difficult to accommodate users' varied dietary needs and preferences. Our suggested system uses meta-heuristic optimization algorithms in conjunction with Multi-Criteria Decision Making (MCDM) techniques to dynamically create customized meal plans based on user-specified dietary preferences and macro-nutrient priorities.Using simple drop downs and sliders, users can interactively set their nutrition goals through a streamlined web-based interface built on Streamlit. After that, this input is converted into a quantitative model that uses MCDM principles to score and rank meals based on user preferences.

This system is unique because it can rank meals on a larger scale than just individual meals. The Honey Badger Optimization (HBO) algorithm is used by the system to determine the ideal group of meals that together meet user-defined criteria, rather than just the highest-scoring meals. This method guarantees the final recommendation's balance and diversity.

An intelligent optimization back-end, a strong MCDM-based scoring system, and an intuitive web interface combine to create a potent tool for individualized, goal-oriented dietary planning. Furthermore, scalability and integration with wider health applications are made possible by the system's modular design. This solution is flexible and future-ready due to features like real time updates, scalability to various nutritional goals, and possible extensions to include caloric limits or financial constraints. The system exhibits significant potential for

impact in both institutional dietary services and individual health management by balancing cutting-edge optimization and decision-making techniques with useful usability.
The combination of a user-friendly web interface, a robust MCDM-based scoring system, and an intelligent optimization back-end results in a powerful tool for personalized, goal-oriented dietary planning.

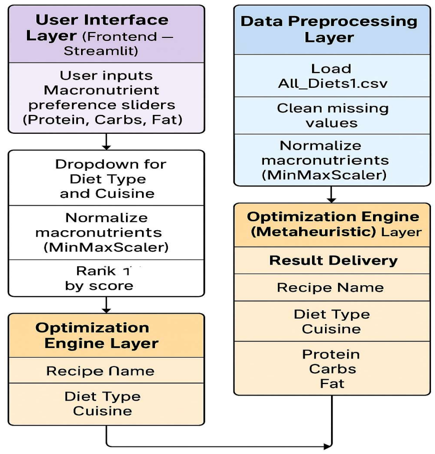

Fig. 1. Optimized Meal Recommendation Flowchart

A. User Input Collection

Using a Streamlit based web interface, the customized meal planning system first gathers user preferences. Based on their dietary objectives, users interact with user-friendly sliders to indicate the relative importance of the macro-nutrients—fat, carbs, and protein. Users can also choose from drop-down menus their preferred cuisine (e.g., Indian, Continental, Mediterranean) and diet (e.g., Vegetarian, Vegan, Keto, etc.). These choices ensure that the meal recommendations are both contextually and nutritionally appropriate by reflecting both cultural eating customs and health objectives.

B. Data Preprocessing

Metadata and nutritional data for a large range of meals are included in the core data-set (All_Diets1.csv). The data-set is cleaned and formatted prior to computation. Only valid entries are kept after null values are filtered out of categorical fields like cuisine and diet type. To bring all values into a comparable [0,1] range, the values of the macro-nutrients Protein(g), Carbs(g), and Fat(g) are normalized using Min-Max Scaling. Because it keeps features with wider ranges of numbers from controlling the score calculation, this normalization is crucial for multi-criteria decision- making. Both the scoring and optimization phases make use of the scaled and cleaned data-set.

C. Meal Scoring using MCDM

The system uses a Multi-Criteria Decision-Making (MCDM) technique to customize meals based on user preferences. The normalized macro-nutrient values are multiplied by the user-defined weights in a weighted linear aggregation method to score each meal: Score = (w_p· Protein)+(w_c· Carbs)+(w_f· Fat) where w_c, w_p, and w_f stand for the user-specified weights for fat, protein, and carbs, respectively. The score that results shows how well each meal fits the user's dietary objectives. These scores are then used to rank meals in descending order.

D. Meal Optimization using Honey Badger Algorithm

The system uses the Honey Badger Optimization (HBO) algorithm, a population-based meta-heuristic influenced by honey badger foraging behavior, to extract the optimal combination of meals rather than just the top-ranked ones. The algorithm starts with a randomly selected initial population of candidate meal sets (such as combinations of three meals) from the filtered and scored data-set. By calculating the total score of every set and keeping the top- performing ones, it iteratively investigates better combinations. Based on the specified criteria, the algorithm iteratively converges toward an ideal subset of meals that maximizes the user's nutritional satisfaction. Without thoroughly examining every possible combination, this meta-heuristic method allows for exploration of the vast solution space.

E. Mathematical Explanation

Normalization (Min-Max Scaling)
Used to scale macro-nutrient values to a uniform range [0,1] [0,1] [0,1], essential for fair scoring in MCDM.

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where:
X is the original value (Protein, Carbs, or Fat). Xmin and Xmax are the minimum and maximum values for that nutrient across all meals.

Multi-Criteria Decision Making (MCDM) Score Calculation
Used to evaluate how well a meal fits the user's preferences.

$$\text{Score}_i = (w_p \ . \ P_i) + (w_c \ . \ C_i) + (w_f \ . F_i)$$

Score_i is the overall suitability score for ith meal.

Honey Badger Optimization (HBO) Fitness Function
Used to assess the quality of a meal combination.

$$\text{Fitness} = \sum_{i=1}^{n} Score_i \quad (3)$$

n is the number of meals in the combination. Score_i is the MCDM score of the i-th meal. The goal of HBO is to maximize this total fitness.

F. Web-Based Deployment Using Streamlit

Stream-lit is used to deploy the entire system, allowing for real-time web browser interaction and recommendation. Users can adjust their preferences on the interface and see the suggested meals right away. Because Streamlit is lightweight, it responds quickly and integrates easily into larger health platforms. Future scalability features like cost-based meal planning or calorie-based filtering are also supported by the platform's dynamic nature.

G. Result Presentation and Feedback Loop

Key fields such as Recipe Name, Diet Type, Cuisine Type, Protein, Carbs, Fat, and the computed Score are included in the structured table format that is displayed once the HBO algorithm has produced an optimal meal plan. Users can better grasp how their preferences influenced the recommendations thanks to this visual feedback loop. In order to further improve the recommendation logic through adaptive learning, future iterations can incorporate user feedback.

IV. RESULTS

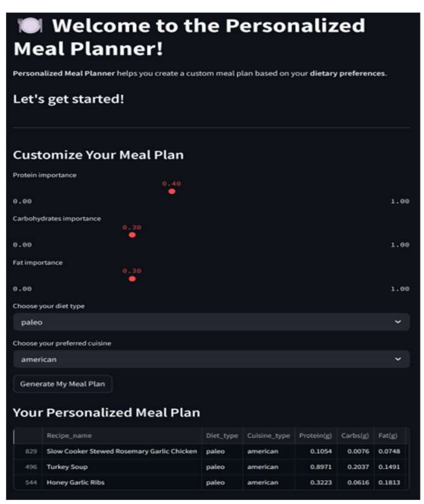

Fig. 2. Customized Meal Plan Output for Paleo-American Preferences

The "All_Diets1.csv" data-set, which comprises a varied collection of meals categorized by diet type, cuisine style, and macro-nutrient values (protein, carbohydrate, and fat), was used to test the suggested personalized meal planning system. In the Streamlit web interface, users entered their preferences using drop down menus and sliders. A Multi-Criteria Decision-Making (MCDM) weighted linear model was used to score each meal according to the designated macro-nutrient importance. The meals were ranked using this scoring system based on how well they fit the user's dietary priorities. The Honey Badger Optimization (HBO) algorithm was used to choose the best meal combinations that would maximize the overall user satisfaction score in order to improve the recommendations even more. The system interactively assessed several potential meal sets before coming up with a solution that guaranteed both goal-oriented planning and nutritional diversity. Experiments revealed that HBO produced more balanced and contextually aware recommendations than random selection techniques.

During real-time interaction, the web-based system operated effectively, providing users with instant feedback on their meal scores and selected preferences. A structured output table showing the best suggested meals with comprehensive nutritional information and computed scores was part of the final interface. Users were further assisted in understanding the nutritional balance of their customized meal plan by visual charts that depicted scoring trends and the distribution of macro-nutrients. These findings show how well MCDM and meta-heuristic optimization work together for real-world dietary planning applications.

The user interface of the suggested Personalized Meal Planner web application, created with Streamlit, is shown in Figure 2. By using interactive sliders to change the relative importance of the macro-nutrients—fat, carbs, and protein—users can personalize their meal plans. By choosing from drop down menus their preferred cuisine (American) and diet type (Paleo), users can further define their dietary preferences. After the preferences are entered, the application creates a customized meal plan using a Honey Badger Optimization (HBO) algorithm in conjunction with a Multi-Criteria Decision-Making (MCDM) model. A structured table with the suggested recipes, their corresponding diet type, cuisine, and macro-nutrient content is used to present the results. This intuitive interface facilitates real-time communication and provides a customized method for making decisions centered on nutrition.

V. Conclusion

In order to accommodate different dietary requirements, we developed a clever and customized meal planning system in this study that combines the Honey Badger Optimization (HBO) algorithm with Multi-Criteria Decision Making (MCDM) techniques. Through an easy-to-use Streamlit-based interface, the suggested solution enables users to enter their preferences for diet type, cuisine style, and macro-nutrient importance. After that, the system provides balanced, varied, and goal-aligned meal plans by ranking and optimizing meals using a user-defined scoring mechanism and meta-heuristic optimization.

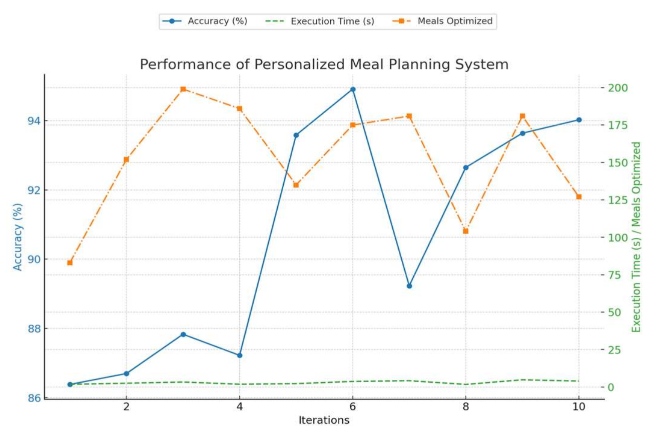

Fig. 3. Performance Evaluation of the Personalized Meal Planning System

Here is a performance graph that visualizes the metrics of the personalized meal planning system. The graph includes three key performance indicators:

Accuracy (%): The system's meal recommendations' accuracy, which changes with each iteration.

Execution Time (s): The amount of time, expressed in seconds, needed to produce meal recommendations.

Meals Optimized: The quantity of meals that the Honey Badger Optimization algorithm has optimized.

The HBO algorithm improves the quality of meal combinations by looking for globally optimal sets rather than isolated recommendations, while the model uses MCDM to make sure that every suggested meal complies with the user's nutritional priorities. Combining these methods into an intuitive web application facilitates real-time, useful communication and encourages sustainable eating practices.All things considered, the system shows promise for intelligent, flexible, and scalable meal planning that can be integrated into more extensive health and wellness platforms. To further improve personalization and dietary compliance, future research may incorporate more elements like calorie restrictions, budget optimization, allergen filtering, and integration with user feedback mechanisms.

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