

AI DIET PLANNER BASED ON USER GOALS

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RELATED WORK

ABSTRACT

This project proposes an AI diet planner that allows users to use user-specific menus depending on the specific destination of each user. H. Weight loss, muscle growth, or a healthy lifestyle. Machine learning and nutrition database algorithms are used to collect and process user-specific information such as age, gender, weight, size, activity level, food preferences, and medical illnesses. The AI algorithm dynamically adapts key nutrients and calorie instructions and provides menus according to the user's goals and preferences. The planner includes adaptive real-time feedback to help users monitor their progress over the long term and reach dynamic nutrition orders. Adaptive solutions are user-oriented and intelligent features for healthier dietary rewards and long-term interventions for wells.

Keyword- Machine Learning K-means.

INTRODUCTION

Given the higher prevalence of lifestyle diseases such as obesity, diabetes and cardiovascular disease, individual and healthy nutrition plans have recently had to be influenced. Traditional recipes for individual size nutrition cannot make personal differences in need, preferences, or metabolism. Further developments in artificial intelligence (AI) and machine learning will revolutionize meal planning by creating adaptive and personalized meals that adapt to the special needs of users. The system determines the optimal calorie and Macron nutritional allocation with user-specific inputs collected and calculated, including demographic data, activity levels, restaurants, and medical status. By using intelligent algorithms, planners generate nutritional diets and adapt recommendations to user performance and feedback. This way users can go beyond nutritional compliance and make sustainable, educated nutritional decisions.

The intersection of artificial intelligence and personalized nutrition has been increasingly explored in recent years to address the limitations of generalized dietary recommendations. Traditional dietary guidelines often overlook individual variability in metabolic profiles, preferences, and health goals. To overcome this, several AI-driven systems have been proposed that apply machine learning to offer customized dietary advice.

Falla et al. (2020) presented a review of machine learning applications in personalized nutrition, highlighting the use of algorithms like decision trees, support vector machines, and neural networks for food classification and nutrient prediction. Lin et al. (2021) developed a smart diet recommendation system based on deep learning, showing significant improvements in the precision of meal planning. However, these systems often focus on direct prediction without robust clustering for user profiling.

Clustering techniques have also been applied in nutritional informatics to group users with similar dietary needs. K-Means has been widely used for this purpose due to its simplicity and efficiency in segmenting large populations (MacQueen, 1967). DBSCAN (Ester et al., 1996) offers advantages in detecting outliers—such as users with rare conditions—while Agglomerative Clustering enables hierarchical grouping, which is useful for multi-level dietary personalization. Despite these advancements, few studies integrate multiple clustering techniques and feedback loops in a unified system, which is the gap this study aims to fill.

OVERVIEW

Diet Planner AI is an intelligent nutritional advisory program that produces tailor-made diets for specific user goals, such as weight loss, muscle building, and general maintenance of health. After receiving user input such as size, gender, weight, age, activity level, food and disease disorders, the program of algorithms for machine learning depends on the full calorie and macro nutritional intake. Next, create a nutritional diet plan that is compatible with the user's



needs and requirements, along with user preferences from a very extensive database for food and nutritional supply. The system also ensures that its nutritional advice is not only scientifically effective, but also realistically realistic for everyday use. One of the main aspects of the system is the adaptive feedback loop. In this case, menus that respond to user and persecution feedback will be adapted for a period of time. Dynamic adaptation allows for continuous improvements in nutritional compliance and performance, ensuring users maintain goal compliance. With the convergence of nutrition science and artificial intelligence, the platform offers an intelligent and scalable solution to the growing demand for TaylorMade health and wellness solutions. The technology can stimulate healthier prevention of living and nutritional diseases bv enabling consumers with implementable personalized nutritional recommendations.

LITERATURE REVIEW

Personalized nutrition has been largely checked in recent years as it offers the potential to improve results from a health perspective through personalising characteristics-based nutrition recommendations. Traditional nutritional recommendations such as tips proposed by public health officials that are not necessarily tailored to fluctuating needs, metabolic responses, and lifestyle factors. Therefore, compliance with such programs has low compliance rates and the results are disappointing. Researchers emphasize the need for individualized nutritional strategies in improving health indicators and maintaining long-term behavior (Ordovas et al., 2018). The implementation of Artificial Intelligence (AI) and Machine Learning (ML) from a health and nutrition perspective has created new opportunities to create adaptive and intelligent systems to deliver nutrition. Experiments have shown that the utility of the AI model predicted calorie needs and determined food classification according to consumption and personalized dietary

or alphabetical values, others, like Screen Resolution and CPU, contain alphanumeric data. Later, these data would require engineering and filtering.

Unused characteristics like "Unamed:0," "Company," and "Product" will be eliminated from the dataset to prevent any issues and forecasts that are prone to errors.

of personalized diet plans. Raw entry data collected by users include demographic attributes (age, gender), anthropometric data (weight, size, BMI), lifestyle factors (physical activity level, sleep time), health indicators (illness, allergies), nutritional preferences (vegetarians, vegetables, etc.), and specific nutritional goals (such as weight loss). Continuous variables such as age and BMI are normalized using MIN-MAX scaling to ensure overall dimension uniformity. Categorical variables including activity level and nutritional preferences are coded for compatibility with clustering algorithms. Additionally, derivative features such as basal metabolic rate (BMR) and total daily energy consumption (TDEE) are calculated to better present individual calorie requirements. These technical features are combined into a comprehensive functional space that effectively improves the capabilities of K-mean, DBSCAN, and cohesive clustering for group users. This structured approach ensures that the model records relevant user features provides and highly adapted nutritional recommendations Explanatory.

DATA ANALYSIS

Exploratory data analysis was performed to understand the underlying patterns and relationships within the user dataset before the clustering algorithm was used. The data records consisted of 500 entries containing variables such as age, gender, BMI, activity level, nutritional preference, and nutritional goals. The first univariate analysis showed that the majority of users in the age group recorded a 40-year decline with a moderate BMI of 26.4. This indicates a slightly overweight trend among the population. The gender distribution is balanced, with the most important part of the user being either registered or slightly active lifestyle. Users with higher activity levels decreased in healthier BMI regions. Visualization instruments such as histograms, box plots, and scatter plots were used to identify outliers and evaluate their properties. For example, outliers were identified by BMI and calorie intake and for special treatment within the cluster. Clustering trends are visually checked in 2D PCA diagrams to reveal the natural groups of users based on BMI, activity level and goals. This analysis helps to check the suitability of data records for unattended learning and lead the selection of characteristics related to clustering and recommendations. EDA results provided important insights informing both functional technology and the structure of the clustering model.

FEATURE ENGINEERING

In this project, functional engineering plays a key role in accurate clustering of users and the generation

DATA PREPROCESSING

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was used. The data records consisted of 500 entries containing variables such as age, gender, BMI, activity level, nutritional preference, and nutritional goals. The first univariate analysis showed that the majority of users in the age group recorded a 40-year decline with a moderate BMI of 26.4. This indicates a slightly overweight trend among the population. The gender distribution is balanced, with the most important part of the user being either registered or slightly active lifestyle. Users with higher activity levels decreased in healthier BMI regions. Visualization instruments such as histograms, box plots, and scatter plots were used to identify outliers and evaluate their properties. For example, outliers were identified by BMI and calorie intake and for special treatment within the cluster. Clustering trends are visually checked in 2D PCA diagrams to reveal the natural groups of users based on BMI, activity level and goals. This analysis helps to check the suitability of data records for unattended learning and lead the selection of characteristics related to clustering and recommendations. EDA results provided important insights informing both functional technology and the structure of the clustering model.

DATA PREPROCESSING

Data preprocessing was a critical step to ensure the quality and consistency of the dataset before applying machine learning models. The raw user data collected included both numerical and categorical features such as age, weight, height, BMI, physical activity level, dietary preferences, and nutritional goals. Initially, missing values were identified and handled using appropriate imputation methods—mean imputation for numerical fields (e.g., weight, height) and mode imputation for categorical fields (e.g., activity level, dietary type). Outliers in numerical features, particularly in BMI and age, were detected using boxplot analysis and addressed through capping or exclusion where necessary to maintain data integrity.

All numerical features were normalized using Min-Max scaling to ensure they contributed equally to distance calculations in clustering algorithms. Categorical features such as gender, activity level, and dietary preferences were transformed into a machinereadable format using one-hot encoding. Additionally, derived attributes such as Basal Metabolic Rate (BMR) and Total Daily Energy Expenditure (TDEE) were calculated using established nutritional formulas to enrich the dataset with goal-specific variables. The final preprocessed dataset provided a clean, scaled, and well-structured input for the K-Means, DBSCAN, and Agglomerative Clustering models, enabling effective user segmentation and personalized diet planning.

MODELLING

The proposed AI-based diet planner's core modeling approach revolves around unmanned

technologies for machine learning aimed at segmenting users based on nutritional needs and personal features. Three clustering algorithms, k-means, dbscan (dense spatial clustering for noise-filled applications), and aggregation hierarchical clustering were used to identify different user groups for personalized nutrition recommendations. The optimal number of clusters was determined using elbow technique and silhouette scores, providing insight into the separation between communities and clusters within the cluster. In contrast to K-means, DBSCAN clusters can discover any form and effectively identify noise in the dataset. This makes it suitable for recording users with rare health conditions or extreme nutritional requirements.

Aggregated cluster formation was used to investigate the hierarchical relationships between user groups. This model constructed dendrograms to visualize nested structures of clusters, enabling fine-tuned segmentation, particularly for personalized recommendations for several levels of granularity. This hybrid modeling approach allowed the system to record a wide range of user profiles and provide a highly personalized nutritional plan.

WEBSITE

This WebApp's user interface is built using the Streamlit library. Stream Lit is an open-source Python library that facilitates the development and dissemination of unique online applications for data science and machine learning.

DEPLOYMENT

The deployment of the AI-based diet planner was designed to ensure accessibility, scalability, and realtime interactivity for end users. The complete system was developed as a web-based application using Streamlit, an open-source Python framework ideal for deploying machine learning models with interactive interfaces. The backend integrates the clustering models (K-Means. DBSCAN. Agglomerative Clustering) and the rule-based diet recommendation engine. The application is hosted on a cloud platform to ensure scalability and uninterrupted access. User inputs-including demographic data, activity level, dietary preferences, and health goals-are collected through intuitive web forms and processed in real-time. The system applies the trained clustering models to assign the user to the appropriate dietary group and generates a personalized meal plan instantly.

To maintain performance and data privacy, the deployment follows best practices in modular design, secure data handling, and efficient model inference. Additionally, a feedback mechanism was integrated to allow users to rate their plans and update their profiles, enabling dynamic model adaptation. This deployment approach ensures that the AI-powered diet planner is

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user-friendly, responsive, and adaptable to various devices and user needs.

RESULT

The proposed AI-controlled diet planner was experimented with a set of 500 users with age, activity level, nutritional habits and health goals. K-Means clustering, DBSCAN clustering, and aggregation clustering are performed, with each model being evaluated by key nutrition groups for user splitting. The best balanced clusters with the greatest similarity within the cluster were created by K-means as validated by a silhouette score of 0.67. DBSCAN correctly marked 8% of users as outliers, either with abnormal nutritional restriction or frequent illness. Aggregated clustering helped to minimize subgroup interulation, particularly using subgroups with high activity and weight loss. The integration of the three models allowed for correct segmentation and increased dietary specificity. Satisfaction was assessed by a 4-week final planning survey and comments. Over 78% of users said they were paying attention to the menu, while 65% showed measurable improvements in achieving their dietary goals. These findings support the effectiveness of a system for creating goal-oriented individual nutritional plans through the adaptive frames with data backed.

The results are displayed in the figures below.

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WORKFLOW DIAGRAM



PREDICTION MODEL



CONCLUSION

This study provides an AI-controlled diet planner that effectively includes machine learning, K-Mean, DBSCAN, and unattended methods of consistent clustering to prepare personalized target-specific diet plans. Through analysis, the system is positioned based on user-specific data such as demographic data, health, lifestyle, and based on tailor-made advice on nutrition planning. Feedback features allow for constant coordination and facilitate user interaction and plan compliance. The results demonstrate the strength to combine AI with nutritional research to promote healthier eating habits and promote coordinated health management. Future research includes real-time



discovery of portable data, increasing food databases, and the use of deep learning models to further improve prediction accuracy and personalization. This system is a simple and scalable solution for digital health interventions to prevent lifestyle illnesses and common fountains.

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