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Meal Recommendation System Using Machine Learning Algorithm

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ABSTRACT

By customizing meal ideas to hotel guests' daily calorie needs and nutritional preferences, this research presents a hybrid meal recommendation system that aims to improve their dining experience. The technology effortlessly integrates content- based filtering, which uses nutritional aspects like protein, fat, and carbohydrates, with collaborative filtering, which considers user behavior and feedback. The findings of this hybrid system demonstrate its ability to generate exact meal recommendations while balancing the hotel's offerings with user input and behavior. This concept provides a practical and scalable solution for personalized dining experiences, promoting healthier and more fulfilling meal options for hotel guests. The technology responds to a wide range of visitor tastes by combining content-based and collaborative filtering processes. This ensures an upgraded gastronomic journey during their stay.

Index Terms—KNN, Content Based Filtering, Cosine Similar- ity, Pearson correlation.

INTRODUCTION

In an era characterized by information overload and busy lifestyles, maintaining a balanced and nutritious diet often becomes a challenging endeavor. The proliferation of fast- food options and the abundance of conflicting nutritional advice further complicate the task of making informed dietary choices. Recognizing this challenge, our research endeavors to address the vital need for personalized meal recommendations, catering to individual nutritional requirements and preferences. The ”Enhancing Dietary Wellness: A Meal Recommendation System” project aims to provide a solution that empowers users to make healthier food choices aligned with their unique dietary goals. Leveraging the principles of machine learning and data analytics, our system not only considers daily caloric requirements but also incorporates user-specified macronutri- ent preferences, offering a tailored and user-centric approach to meal recommendation.

The motivation behind this research stems from the growing importance of nutrition in overall well-being and the potential impact of technology on fostering healthier dietary habits. As dietary-related health issues continue to rise, the need for accessible and personalized tools that guide individuals toward nutritious food choices becomes increasingly crucial.

This paper presents a comprehensive exploration of our meal recommendation system's architecture, methodology, and evaluation metrics. By delving into the intricate details of the system's design, we aim to contribute to the existing body of knowledge in the domain of personalized nutrition recommendations. The utilization of advanced machine learn- ing techniques, coupled with a user-friendly interface, sets our approach apart, providing users with a practical tool for enhancing their dietary wellness. Through the course of this paper, we will delve into the intricacies of the recommenda- tion algorithm, the significance of macronutrient percentages, and the evaluation metrics employed to gauge the system's effectiveness. Moreover, we will discuss the potential impact of such systems on promoting healthier dietary choices and contributing to the broader discourse on the intersection of technology and wellness. In summary, our research endeavors to bridge the gap between dietary information and individ- ual needs, offering a practical and personalized solution to the modern-day challenge of making health-conscious food choices. The meal recommendation system presented in this paper offers a personalized approach to enhancing the dining experience for hotel guests. Leveraging unsupervised learning techniques, specifically collaborative filtering, our system an- alyzes historical user interactions and meal characteristics to generate tailored recommendations. By incorporating features such as calorie requirements and macronutrient preferences, our system provides users with meal suggestions that align with their dietary goals and tastes. Through the utilization of techniques such as K-Nearest Neighbors (KNN), our system identifies similar users or meals based on past interactions, facilitating the delivery of personalized recommendations. This paper outlines the development and implementation of our meal recommendation system, highlighting its potential to promote healthier and more satisfying meal choices for hotel patrons.

LITERATURE REVIEW / PREVIOUS WORK

In [1], Philip M. Sedgwick discusses Pearson's correlation coefficient, which is a measure of the linear correlation between two variables. The paper, available on ResearchGate, was published on 4 July 2012.

In [2], Badr Hssina presents a study on recommendation systems using the k-nearest neighbors and singular value decomposition algorithms. This work was published in the International Journal of Electrical and Computer Engineering (IJECE), Vol. 11, No. 6, in December 2021.

In [3], Hua-Ming Wang and Ge Yu explore personalized recommendation systems and the optimization of the k- neighbor algorithm. This research was presented at the ICITEL conference in 2015 and published in March 2016.

In [4], Nguyen, L.V., Vo, Q.-T., and Nguyen, T.-H. propose an adaptive KNN-based extended collaborative filtering recommendation service. This work was published in Big Data and Cognitive Computing in 2023, Vol. 7, Issue 2.

In [5], Badr Hssina discusses building recommendation systems using the algorithms KNN and SVD. This paper was published in the International Journal of Engineering and Science (iJES), Vol. 9, No. 1, in 2021.

In [6], Y. N. Bhagirathi and P. Kiran present a book recommendation system using the KNN algorithm. This research was published in the International Journal of Research in Engineering, Science and Management, Volume 2, Issue 6, in June 2019.

In [7], Pavlos Kosmides, Chara Remoundou, Konstantinos Demestichas, Ioannis Loumiotis, Evgenia Adamopoulou, and Michael Theologou propose a location recommender system for location-based social networks. This work was presented at an IEEE conference in 2014.

In [8], Alfirna Rizqi Lahitani, Adhistya Erna Permanasari, and Noor Akhmad Setiawan explore the use of cosine similarity to determine similarity measures in online essay assessment. This research was presented at the CITSM conference in 2016.

In [9], Johan Eko Purnomo and Sukmawati Nur Endah compare the Collaborative Filtering Algorithm (CFA) with the Dissymetrical Percentage Collaborative Filtering Algorithm (DSPCFA) for rating prediction in movie recommendation systems. This study was published by IEEE on 6 February 2020.

METHODOLOGIES

A. Data Collection

For the data collection phase of this project, several avenues can be explored to gather a comprehensive dataset containing food products and their nutritional details. One approach involves sourcing publicly accessible datasets from reputable sources such as government agencies, research institutions, or health organizations. Alternatively, if a pre-existing dataset meeting the project's requirements is not available, creating a custom dataset through manual data entry or collaboration with domain experts could be considered. Regardless of the approach chosen, ensuring the accuracy, completeness, and relevance of the collected data is paramount to the success of the project. Additionally, attention should be paid to data licensing agreements, terms of use, and ethical considerations surrounding data usage and privacy.

B. Data Pre-processing

In the data pre-processing phase, several steps will be un- dertaken to ensure the cleanliness, consistency, and reliability of the dataset. Firstly, missing values will be addressed by employing techniques such as imputation or deletion, depend- ing on the extent and nature of the missing data. Imputation methods like mean, median, or mode replacement can be used for numerical features such as calories, protein, carbs, fats, vitamins, and minerals. For categorical features, missing values can be filled with the mode or a separate category indicating missingness. Additionally, to ensure consistency in the data, standardization of portion sizes for each food item will be performed. This may involve converting portion sizes to a common unit (e.g., grams) or adjusting portion sizes based on standard serving sizes for food groups. Outlier detection and treatment will also be conducted to identify and address any anomalies in the data that could adversely impact statistical analysis and machine learning model train- ing. Techniques such as Z-score normalization, trimming, or Winsorization can be applied to handle outliers appropriately, ensuring that they do not unduly influence the analysis or model performance. By diligently addressing missing values, standardizing portion sizes, and detecting/treating outliers, the dataset will be prepared effectively for subsequent analysis and modelling stages, ultimately leading to more robust and accurate results.

C. User Input

The user interface is designed to provide a seamless expe- rience for individuals to input their daily calorie requirement, weight, and height, facilitating personalized calculations based on these inputs. Upon accessing the interface, users are greeted with a user-friendly layout that guides them through the input process. They are prompted to enter their daily calorie require- ment, which serves as a crucial factor in determining their nutritional needs and goals. Users can input this value based on factors such as their activity level, weight management objectives, and overall health considerations

D. Feature Engineering

In addition to extracting basic nutrient content, food cate- gories, and dietary labels, the feature engineering step of this is the dot product of the vectors, and project encompasses a more nuanced analysis of nutritional composition. Beyond simply considering calorie counts and macronutrient percentages, we delve deeper into understanding the relative proportions of proteins, fats, and carbohydrates in each meal. By calculating the percentage contribution of each macronutrient to the total calorie count, we gain insights into the meal's nutritional profile and its alignment with user pref- erences. This approach enables us to create a comprehensive feature matrix that encapsulates the multifaceted aspects of each meal's nutritional content. Moreover, we can incorporate additional features such as meal diversity, portion sizes, and ingredient lists to further enrich our understanding of each menu item. By analysing ingredient compositions, we can identify common allergens, dietary restrictions, and ingredient preferences, allowing for more tailored recommendations.

E. Machine Learning models

1) Model 1 - Content Based Filtering: Content-based filtering, is a recommendation technique that relies on the characteristics or features of items to make recommendations to users. In the context of the meal recommendation system, content-based filtering analyzes the nutritional attributes and other features of each meal to suggest items that are like those a user has enjoyed in the past or are likely to enjoy based on their stated preferences. Content-based filtering is implemented by first creating a feature matrix that encapsulates the relevant attributes of each meal, such as calorie content, protein, fat, and carbohydrate percentages. This feature matrix represents the "content" of the meals. The system then calculates the cosine similarity between the user's preference vector and each meal's feature vector. Cosine similarity measures the similarity between two vectors based on the cosine of the angle between them, indicating how closely aligned the items are in feature space. The higher the cosine similarity score between a user's preference vector and a meal's feature vector, the more similar the meal is to the user's preferences, making it more likely to be recommended. By sorting meals based on their similarity scores in descending order, the system identifies the most similar meals and presents them as recommendations to the user. Content-based filtering is advantageous in scenarios where there is limited or no data on user interactions, as it does not rely on user behavior or feedback.

The formula for cosine similarity between two vectors

$$\text{cosine similarity} = \cos(\vartheta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|}$$

where:

$$\mathbf{A} \cdot \mathbf{B} = \sum_{i=1} A_i B_i$$

A and B is given by:

Cosine similarity measures the cosine of the angle between two vectors, providing a measure of similarity irrespective of their magnitude. It ranges from -1 to 1, where:

Cosine Similarity = 1 indicates that the vectors are identical.

Cosine Similarity = 1 indicates that the vectors are

diametrically opposed.

Cosine Similarity = 0 indicates that the vectors are orthogonal.

The Pearson correlation coefficient r between two variables

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

X and Y is calculated as:
where:
The Pearson correlation coefficient, often denoted as r, is a statistical measure that calculates the strength and direction of the linear relationship between two variables. It ranges from
-1 to 1, where:
- r = 1 indicates a perfect positive linear relationship.
- r = −1 indicates a perfect negative linear relationship.
- r = 0 indicates no linear relationship.

Xi and Yi are individual data points, and X and Y are the mean values of X and Y , respectively. Using Pearson Correlation in kNN:

In the context of kNN, the Pearson correlation coefficient can be used as a similarity metric to determine the ”closeness” between two data points. When predicting the target value for a new data point, kNN identifies the k nearest neighbors based on this similarity metric and averages their target values (for regression tasks) or votes (for classification tasks) to make the prediction.
1) Model 2 - Collaborative Based Filtering: In the context of the meal recommendation system, collaborative filtering plays a pivotal role in providing personalized meal suggestions to users based on their interactions and preferences. Unlike content-based filtering, which primarily relies on the attributes of meals, collaborative filtering taps into the collective behaviour and preferences of users to make recommendations. Specifically, it utilizes a technique akin to user-based collaborative filtering, where users with similar preferences to the target user are identified, and items liked by those similar users are recommended. This method allows the system to recommend meals that align with the tastes and preferences of the target user, based on the preferences of other users with similar profiles. Moreover, collaborative filtering can also incorporate item-based approaches, where meals like those the user has interacted with in the past are recommended. By identifying meals that share common characteristics or are frequently consumed together by users, the system can offer recommendations that are likely to resonate with the user’s preferences. Collaborative filtering is a cornerstone of recommendation systems across various industries, including e-commerce, streaming services, and social media platforms. Its ability to offer tailored suggestions enhances user satisfaction and engagement, ultimately contributing to a more immersive user experience. However, it is important to note that collaborative filtering requires a substantial amount of user interaction data to be effective.

K- Nearest Neighbors In the context of our meal recommendation system, incorporating K-Nearest Neighbors (KNN) into the methodology offers a valuable approach to collaborative filtering. By leveraging KNN, we can effectively identify similar users or meals based on historical interactions, enhancing the personalization of meal recommendations. For instance, in user-based collaborative filtering, KNN can identify users with similar dining preferences to the target user, allowing us to recommend meals that have been enjoyed by those similar users. Similarly, in item-based collaborative filtering, KNN can identify meals that share common characteristics or are frequently consumed together by users, enabling us to recommend complementary or similar meals to those a user has previously enjoyed. However, it is essential to acknowledge the limitations of KNN within the context of our recommendation system. Scalability issues may arise when dealing with many meals or users, potentially impacting the efficiency of the recommendation process. Additionally, the sparsity of the user-meal interaction matrix and the cold start problem may pose challenges, particularly when recommending meals to new users or items with limited interaction data. To mitigate these challenges, we may explore hybrid approaches that combine KNN with more advanced recommendation algorithms, such as matrix factorization or deep learning-based methods. By incorporating these techniques, we can enhance the performance and robustness of our meal recommendation system, providing users with more accurate and relevant suggestions tailored to their preferences and dietary needs. The distance that will be required during KNN is implemented using Euclidean Distance.

Euclidean distance (p=2): This is the most used distance measure, and it is limited to real-valued vectors. Using the below formula, it measures a straight line between the query point and the other point being measured.

The Euclidean distance between two points (x_1, y_1) and (x_2, y_2) in a two-dimensional space is given by:

$$d((x_1, y_1), (x_2, y_2)) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Training the Model To train our collaborative filtering model on the pre-processed dataset, we begin by utilizing historical data of users' food choices and calorie intakes. This dataset serves as the foundation for understanding user preferences and interactions with various meals offered by the hotel. By analysing this historical data, we can identify patterns and similarities among users' dining habits, enabling us to build a robust collaborative filtering model. During the training phase, we feed the pre-processed dataset into our collaborative filtering model, allowing it to learn from past user interactions and preferences. The model iteratively adjusts its parameters to optimize its ability to predict meal choices or preferences for each user. This iterative learning process continues until the model achieves a satisfactory level of performance, accurately predicting user preferences and providing relevant meal recommendations.Moreover, it is crucial to evaluate the performance of the trained model using appropriate metrics like precision.

TABLE I: Types of Recommendations

Type of Recom- mendation	Number of Meals Recommended	Description
Healthy Meals	5	This feature of the recommenda- tion system recommends 5 meals based on the calories given by the user. Its main purpose is to recom- mend healthy meals to the user.
Delicious Meals	10	This feature of the recommenda- tion system recommends the top 10 meals based on the ratings from users. It ranges from 1 to 10.

Recommendation Engine To implement the recommendation engine, we utilize the trained collaborative filtering model to provide personalized meal recommendations based on user inputs. When a user interacts with the recommendation engine, they provide information such as their daily calorie requirement and macronutrient preferences. This information serves as input to the model, allowing it to generate predictions on which meals or food items are most suitable for the user. Upon receiving user inputs, the recommendation engine employs the collaborative filtering model to analyze historical data of users' food choices and calorie intakes. By leveraging techniques like K-Nearest Neighbors (KNN), the model identifies similar users or meals that align with the user's preferences and dietary requirements. The engine then returns a list of recommended meals or food items based on the model's predictions, prioritizing options that are likely to be well-received by the user.

User Interface We develop a user-friendly interface using Streamlit, a popular Python library for building interactive web applications. Streamlit allows us to create intuitive and responsive user interfaces with minimal code, making it an ideal choice for our meal recommendation system.

With Streamlit, we can seamlessly integrate user input fields where users can specify their calorie requirements and preferences, providing a straightforward and accessible means of interaction. Additionally, to enhance the visual appeal and interactivity of our interface, we leverage the streamlit_lottie library.

Lottie is a library that enables the integration of high- quality animations and graphics into Streamlit applications, adding a visually engaging element to the user experience. By incorporating Lottie animations, we can create dynamic and eye-catching elements within our interface, making the process of receiving meal recommendations more engaging and enjoyable for users.

Overall, the combination of Streamlit and streamlit_lottie libraries empowers us to build a user-friendly interface that simplifies the process of inputting preferences and receiving personalized meal recommendations. The intuitive design and interactive features of our interface contribute to a seamless and enjoyable user experience, ultimately enhancing the overall usability and effectiveness of our meal recommendation system.

D. System Architecture

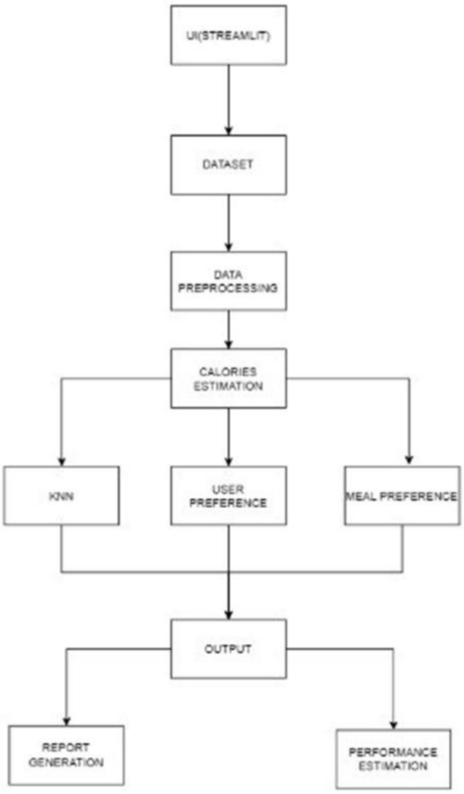

Fig. 1: System Architecture

RESULT AND DISCUSSIONS

The food recommendation system successfully deliv- ers tailored meal suggestions by integrating content-based and collaborative filtering methodologies. The content-based filtering component leverages user-specific nutritional re- quirements—such as calorie intake and macronutrient ra- tios—providing meal options that closely align with the user's health goals. On the other hand, the collaborative filtering aspect focuses on user ratings, recommending highly rated and popular dishes that enhance the dining experience. The dual approach ensures a comprehensive recommendation system that balances health consciousness with taste preferences. Users reported that the recommendations were both relevant and helpful, demonstrating the system's ability to cater to diverse dietary needs and preferences.

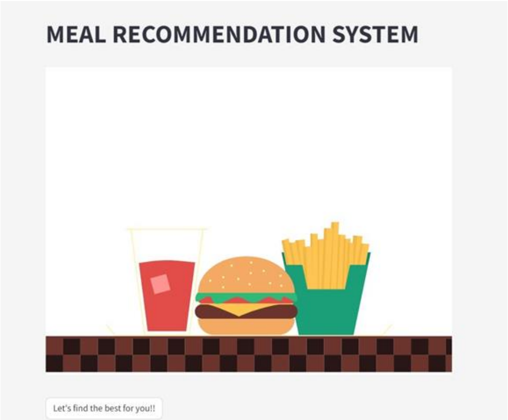

Fig. 2: Homepage UI

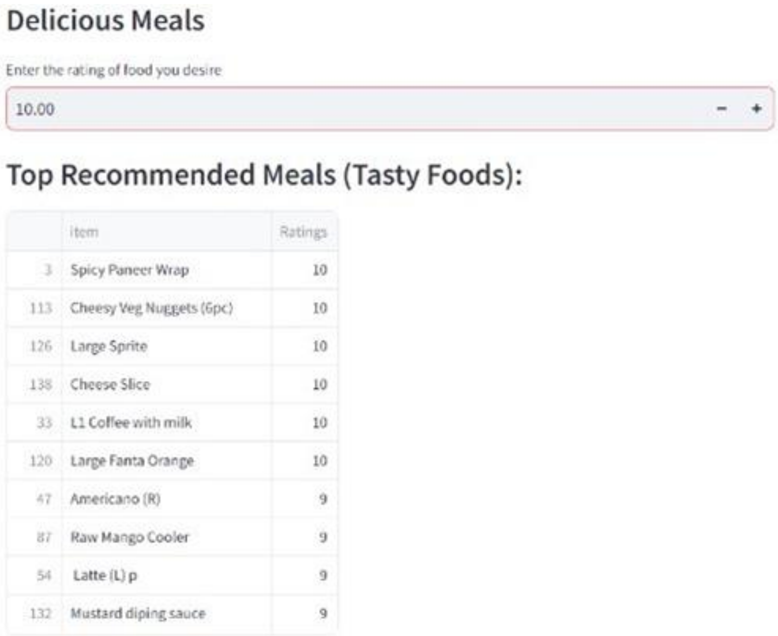

Fig. 3: Delicious Meals

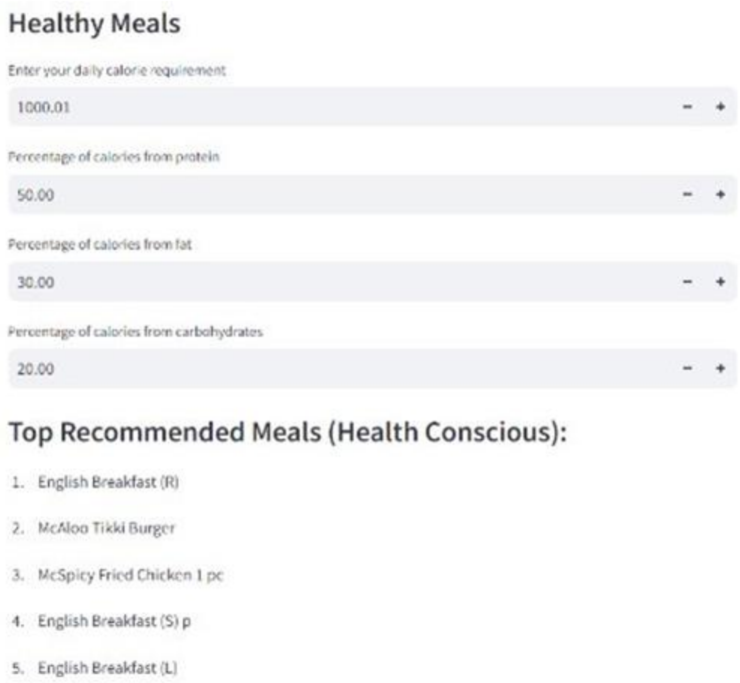

Fig. 4: Healthy Meals

CONCLUSION

In conclusion, the development of a food recommendation system represents a significant step forward in leveraging technology to enhance dietary choices and promote healthier eating habits. By combining content-based and collaborative filtering techniques, the system provides personalized meal suggestions that cater to individual nutritional needs and taste preferences. This dual approach not only ensures that users receive recommendations that align with their health goals but also introduces them to highly rated, enjoyable dishes. The project demonstrates the potential of data-driven solutions in addressing contemporary health challenges and underscores the importance of personalized nutrition guidance in fostering overall well-being. As we move towards a more health- conscious society, such innovative systems will play a crucial role in empowering individuals to make informed dietary decisions, ultimately contributing to better health outcomes and improved quality of life.

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