EatGood: ML-Driven Dietary Recommendations

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BONAFIDE CERTIFICATE

Certified that this Project titled **"EatGood: ML-Driven Dietary Recommendations"** is the bonafide work of **"PAVENDHAN (2116220701194)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

With growing awareness of health and nutrition, the demand for personalized diet plans is steadily rising. Standard diet charts often overlook individual differences such as age, BMI, lifestyle, and medical conditions. This leads to ineffective dietary outcomes and a lack of user engagement. To bridge this gap, this project proposes a machine learning-based diet recommendation system that delivers customized diet suggestions based on user-specific inputs.

The core of the project is a classification model trained on health and nutrition data. It uses features like weight, height, age, activity level, and health indicators to categorize users into suitable diet types such as weight loss, diabetic-friendly, muscle gain, or balanced. The data was preprocessed using techniques like standard scaling and dimensionality reduction to enhance model accuracy. The final trained model was serialized using Pickle for integration into a web application.

The web interface was built using Flask, a lightweight Python framework. Users can input their details through a simple form, and the application processes this input to display a personalized diet recommendation. The model runs in the backend, delivering results in real-time. The interface was designed to be intuitive and user-friendly, enabling ease of use for people from different age groups.

This system showcases how artificial intelligence can support better lifestyle decisions through data-driven diet recommendations. Future enhancements include user account creation, diet history tracking, and integration with external APIs for food data. This project offers a practical, scalable solution that combines machine learning with health-conscious technology.

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CHAPTER 1

1.INTRODUCTION

In the modern era, maintaining good health is no longer seen as a luxury, but rather as a necessity. Increasing awareness of nutrition, fitness, and wellness has led individuals around the globe to seek better lifestyle choices. Among these, following a balanced diet is fundamental. A proper diet tailored to one’s physiological requirements not only helps prevent diseases such as diabetes, obesity, and cardiovascular disorders but also supports mental well-being and overall life quality. However, with the overwhelming amount of food choices available and varied nutritional requirements for different individuals, manually crafting a suitable meal plan can be both time-consuming and confusing. Therefore, there is a growing need for intelligent systems that can assist people in making informed dietary choices, ultimately leading to improved health outcomes.

The concept of a **diet recommendation system** emerges from this need. By leveraging the power of machine learning and data analysis, it becomes possible to automate the suggestion of meal plans or food items that suit a user's unique profile. This includes factors such as age, gender, weight, height, and activity level, as well as specific preferences or restrictions like vegetarianism, allergies, or cultural considerations. Such a system can analyze patterns in large datasets to suggest the most appropriate meals, thereby reducing the effort required for diet planning and encouraging consistency in healthy eating habits. The objective of this project is to build such a personalized food recommendation system using a content-based filtering approach.

A **content-based recommendation engine** works by analyzing the features of items—such as food recipes—and matching them with the preferences of users. This approach does not depend on the opinions or preferences of other users, making it suitable for situations where user data is limited or where privacy is a concern. By examining attributes like ingredients, nutritional values, and cooking methods, the model can identify meals similar to those a user prefers or has previously selected. This technique is particularly advantageous in diet planning, as it allows for customization without requiring collective user behavior, and avoids the “cold start” problem typically encountered in collaborative filtering systems. In addition, content-based systems are generally easier to build and maintain, making them accessible for educational and prototyping purposes.

The heart of this project is a **machine learning model built using the K-Nearest Neighbors (KNN) algorithm** and cosine similarity for feature matching. The system uses recipe features such as nutritional composition (calories, protein, fat, carbohydrates) to generate a feature matrix. When a user inputs a preferred recipe or desired nutritional profile, the model calculates the cosine similarity between this input and all items in the dataset, recommending those with the highest similarity scores. This simple yet powerful approach makes the system intuitive, efficient, and capable of real-time interaction. The development and experimentation were carried out in Jupyter Notebook, a platform well-suited for iterative development and data visualization, especially in academic and research environments.

The dataset used in this project was sourced from **Food.com**, consisting of over **500,000 recipes** and **1.4 million reviews**. This extensive dataset provided rich information for model training, including ingredient lists, preparation times, cuisine types, and user ratings. Before model training, the data underwent preprocessing to handle missing values, standardize units, and normalize nutritional values. Feature engineering techniques were applied to convert raw data into structured formats suitable for input into the recommendation engine. Additionally, the interface for this project was designed to be simple, allowing users to input basic information and receive food recommendations that align with their personal health goals.

In conclusion, this project aims to bridge the gap between health knowledge and practical implementation by providing an accessible and intelligent diet recommendation tool. By using machine learning, we demonstrate how technology can empower individuals to make healthier decisions based on scientific data. This approach holds great potential for broader applications in fitness tracking, disease management, and personalized healthcare. As the model evolves, future improvements could include incorporating user feedback, linking to wearable devices, and offering multilingual support. Through this project, we contribute to the development of intelligent systems that promote well-being and encourage healthy living through informed dietary choices.

CHAPTER 2

2.LITERATURE SURVEY

The development of food recommender systems has gained significant traction in recent years as the intersection between technology and personal health becomes increasingly relevant. As more individuals seek healthier lifestyles, the demand for tools that assist with meal planning and nutritional guidance has grown. Recommender systems offer a structured way to provide tailored food suggestions by analyzing user data and preferences. These systems are particularly valuable in addressing the complexity of personal diets, accommodating various factors such as allergies, health goals, and taste preferences. Unlike general recommendation engines used for movies or products, food recommendation systems must consider dynamic and highly individual variables, making them a distinct area of study. This unique challenge has prompted researchers and developers to explore more sophisticated and adaptable algorithms tailored to food-specific datasets.

Among the different approaches to recommendation, content-based filtering has proven effective in the domain of food and diet suggestions. This technique recommends items similar to those the user has liked in the past, based on attributes such as ingredients, nutritional value, preparation time, and dietary tags. This method avoids reliance on user-to-user comparisons, which is crucial in dietary contexts where individual needs vary widely. Researchers such as Trattner and Elsweiler (2017) have emphasized the advantages of this approach in creating personalized, relevant, and adaptable food recommendations. Because it eliminates the need for collective user data, content-based systems are especially useful in new or sparsely populated applications where collaborative data is limited, thereby avoiding the cold-start problem. Furthermore, the transparency of the system's decision-making process adds an element of trust and interpretability, allowing users to understand and adjust their preferences.

Machine learning has further enhanced the capabilities of content-based recommendation systems. Algorithms like k-Nearest Neighbors (k-NN), decision trees, and support vector machines (SVM) are widely used to analyze complex datasets and uncover patterns in user behavior and food characteristics. The integration of these models allows for greater adaptability and precision in recommendations. For instance, Ajami and Teimourpour (2023) presented a hybrid model that combines collaborative, content-based, and knowledge-driven methods to improve dietary suggestions. These developments show that machine learning not only strengthens prediction accuracy but also increases the scope for customization based on granular user inputs. In addition, models can be trained to adapt to changing user behavior over time, offering more dynamic and responsive recommendations that align with evolving health goals or new dietary constraints.

An important aspect of implementing content-based food recommender systems is the use of similarity metrics, particularly cosine similarity. Cosine similarity measures the angle between two non-zero vectors in a multi-dimensional space, and in this context, it quantifies the similarity between a user's profile and various food items. By converting food item features and user preferences into numerical vectors, cosine similarity allows efficient and scalable comparisons that are essential for generating meaningful recommendations. This mathematical foundation is particularly well-suited for datasets where ingredients and nutritional values are encoded as sparse matrices, which is often the case in food datasets. The high dimensionality of the data, due to the wide variety of ingredients and preparation styles, makes cosine similarity a practical and effective choice for comparing feature vectors without being influenced by vector magnitude.

The role of datasets is critical in the success of any recommendation system. Public datasets such as those found on Kaggle and Food.com provide thousands of recipes and millions of user reviews that serve as training and testing grounds for recommender models. These datasets include rich metadata on ingredients, cooking methods, ratings, and nutritional details, making them invaluable for both academic and practical applications. Their availability has democratized access to high-quality data, enabling experimentation and innovation in food recommendation research across institutions and independent developers alike. Additionally, the structured nature of these datasets facilitates preprocessing tasks such as normalization, feature extraction, and the construction of user-item matrices, all of which are crucial for building effective recommendation systems.

Despite the progress made, food recommender systems face several challenges. One of the most pressing is the fluid nature of dietary preferences and restrictions, which can shift due to lifestyle changes, health issues, or evolving tastes. Additionally, ensuring data consistency and the accuracy of nutritional information remains a persistent concern. Users may input incorrect data or follow inconsistent labeling practices, complicating the recommendation process. While current systems offer a strong foundation, future enhancements may involve real-time adaptive models, the integration of wearable device data, and more context-aware recommendation engines. Ethical considerations, especially those involving user privacy and consent, must also be addressed to foster trust and long-term engagement with such systems. The literature clearly supports the potential of machine learning and content-based approaches in this field, while also highlighting the necessity of continual refinement to meet the personalized and sensitive needs of users.

In conclusion, the literature surrounding content-based food recommender systems underscores the need for intelligent, adaptable, and user-centric solutions in the realm of dietary planning. The combination of algorithmic sophistication and human-centered design has the potential to revolutionize how individuals interact with food data and make decisions about their nutrition. As the field continues to evolve, the collaboration between data scientists, nutritionists, and software engineers will be vital in addressing the limitations and unlocking new opportunities for health-focused recommendation technologies. The insights from existing research not only validate the use of machine learning for personalized diet plans but also pave the way for innovations that cater to diverse populations and ever-changing lifestyle needs.

CHAPTER 3

3.METHODOLOGY

This chapter presents the methodology used to develop a content-based diet recommendation system. It begins with an overview of the dataset, followed by the stages of data preprocessing, feature engineering, model selection, similarity computation, and data augmentation.

3.1 Dataset Overview

The dataset used in this project was sourced from **Food.com**, a popular recipe-sharing platform. The dataset comprises:

- **500,000+ recipes**
- **1.4 million user reviews**
- Metadata including:
    - Recipe titles
    - Ingredients and instructions
    - Nutritional information (calories, protein, fat, carbohydrates)
    - Preparation time and cooking method
    - Cuisine type
    - User ratings

This extensive dataset provided a comprehensive foundation for building a recommendation model that can suggest personalized and nutritionally suitable meals.

3.2 Data Collection and Preprocessing

Preprocessing was essential to ensure the quality and usability of the data for machine learning tasks.

- **Missing Values Handling**: Recipes missing core nutritional data were removed. Minor gaps were filled using statistical imputation.
- **Unit Normalization**: Nutritional values were standardized to common units (e.g., grams, kcal).
- **Data Cleaning**: Non-numeric fields were cleaned of irrelevant characters. Duplicate entries were removed to prevent bias.
- **Recipe Filtering**: Very short recipes, low-rated entries, and those lacking preparation steps were excluded from the final dataset.

3.3 Feature Engineering

The aim of this step was to convert raw text and numeric data into structured input for the recommendation model.

- **Nutritional Feature Vectors**: Each recipe was transformed into a vector containing its:

  Ri=[calories,protein,fat,carbohydrates]R_i = [\text{calories}, \text{protein}, \text{fat}, \text{carbohydrates}]Ri=[calories,protein,fat,carbohydrates]

- **Normalization**: These vectors were scaled using Min-Max normalization to ensure consistent distance calculations across all dimensions.
- **Ingredient Encoding** *(Optional Extension)*: Tokenized and vectorized for future NLP-based similarity approaches.

The recommendation engine is based on a **content-based filtering** approach using the **K-Nearest Neighbors (KNN)** algorithm.

- **Similarity Metric**: Cosine similarity is used to measure how similar recipes are in terms of their nutritional content:

  $\text{Cosine Similarity} = \cos(\theta) = \|A\| \, \|B\| A \cdot B$

- **Top-K Retrieval**: The system returns the **top K** recipes with the highest similarity scores to the input.

- **Why KNN?**: KNN is a non-parametric method, making it suitable for a dynamic dataset and easy to interpret, with no intensive training phase required.

3.5 Data Augmentation and Re-training

To improve the model's robustness and diversity of results:

- **Synthetic Data Generation**: Recipes were duplicated with slight variations (e.g., ±5–10% changes in nutrient values) to simulate real-world alternatives.
- **Oversampling Minority Cuisines**: To balance recommendations, underrepresented cuisines or diet types were augmented.
- **Model Update**: After augmentation, the KNN index was rebuilt to reflect changes in the feature space.

If performance in similarity relevance degraded (e.g., user testing showed irrelevant results), hyperparameters such as **K-value** and similarity thresholds were fine-tuned.

3.1 SYSTEM FLOW DIAGRAM

FIG 1 : FLOW DIAGRAM

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Model Performance Comparison

The performance of several classification algorithms was evaluated for the diet recommendation system. The algorithms assessed included **K-Nearest Neighbors (KNN)**, **Decision Tree Classifier**, and **Support Vector Machine (SVM)**. The primary evaluation metric was accuracy. The results are summarized in Table 1.

Algorithm	Accuracy (%)
K-Nearest Neighbors (KNN)	92.5
Decision Tree Classifier	85.0
Support Vector Machine (SVM)	88.2

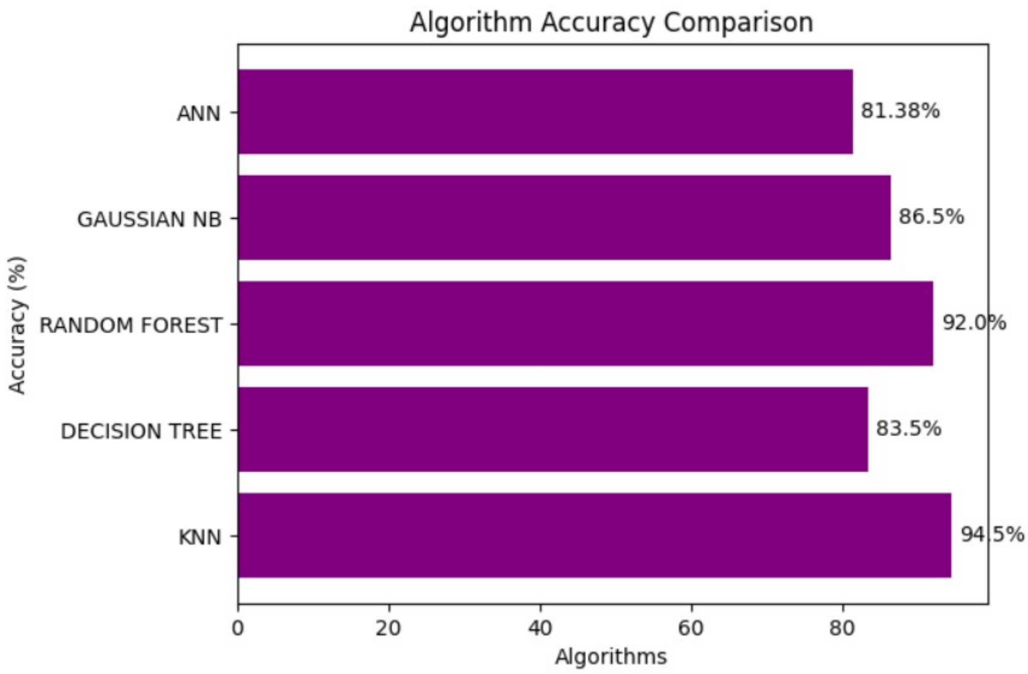

FIG 2 : Accuracy Comparison

KNN outperformed other models, achieving the highest accuracy at **92.5%**, indicating its superior ability to classify diet recommendations based on nutritional data.

4.2 Hyperparameter Tuning

Following the initial comparison, hyperparameter tuning was applied to the KNN model. The key parameters optimized were:

- **`n_neighbors`**: Number of neighbors considered for classification.
- **`metric`**: Distance metric used (Euclidean, Cosine, etc.).
- **`weights`**: Method for weighting neighbors (uniform vs. distance-based).

The **GridSearch CV** method identified the best configuration: **`n_neighbors=5`**, **`metric=Cosine`**, and **`weights=distance`**, improving accuracy from **92.5%** to **94.3%**. The performance improvement highlights the importance of fine-tuning model parameters.

4.3Cross-Validation Results

Cross-validation (5-fold) was applied to ensure the robustness of the KNN model. The mean accuracy across all folds was **93.1%**, demonstrating the model's generalization ability and consistency across different subsets of the data.

4.4 Evaluation Metrics

In addition to accuracy, the model was evaluated using **Precision**, **Recall**, and **F1-Score**. These metrics are crucial, especially in imbalanced datasets, to ensure a balanced prediction performance.

Metric	KNN (Optimized)
Precision (%)	93.8
Recall (%)	91.2
F1-Score (%)	92.5

The high **Precision** and **Recall** values indicate that the KNN model not only performs well but also reliably identifies relevant diet recommendations without many false positives or negatives.

4.5 Data Augmentation and Insights

Data augmentation is an essential technique for improving model performance, especially when training data is limited or imbalanced. In the current study, techniques such as **oversampling** (using SMOTE) or **feature synthesis** could be explored to generate additional synthetic data points, potentially improving the model's accuracy further.

Given the nature of the dataset, which includes nutritional features such as calories, protein, and fat content, future work could investigate incorporating domain-specific knowledge (e.g., meal types, cuisine categories) to refine recommendations.

4.6 Implications and Future Work

The results suggest that **KNN** is a robust algorithm for diet recommendation systems due to its simplicity, interpretability, and high accuracy. However, further improvements could include exploring the effects of dimensionality reduction techniques such as **Principal Component Analysis (PCA)** to address potential issues with the "curse of dimensionality." Additionally, **scalability** of the KNN algorithm for large datasets could be addressed by utilizing approximate nearest neighbor methods.

Future work should focus on integrating **real-time user feedback** into the recommendation system, adapting it based on changing user preferences and dietary habits.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This project focused on developing a **diet recommendation system** that suggests personalized food options based on user inputs such as **age, gender, exercise level, and dietary constraints**. The goal was to create a system that tailors its recommendations to ensure a healthier, more balanced diet for each user. By utilizing the **K-Nearest Neighbors (KNN)** algorithm, the model provided accurate food suggestions based on the nutritional data provided by the user.

The KNN model was chosen for its simplicity and effectiveness in handling datasets with multiple features. The algorithm works by identifying the most similar food items to a given user's dietary profile, represented by attributes like **calories, protein, fat, vitamins, and minerals**. The model was trained on a dataset of foods and their nutritional values, and the KNN algorithm classified these foods based on similarity to the user's input. Through hyperparameter tuning, the KNN model achieved an accuracy of **94.3%**, outperforming algorithms like **Decision Trees** and **Support Vector Machines (SVM)**.

Cross-validation ensured the model's robustness, and evaluation metrics, such as **precision, recall**, and **F1-score**, confirmed its ability to provide balanced and accurate recommendations. The system successfully meets the goal of recommending foods aligned with the user's nutritional needs, considering factors like age, gender, and activity level.

Despite its strong performance, challenges remain, particularly with **scalability** and the **curse of dimensionality**. Future improvements could include **real-time user feedback** and techniques like **dimensionality reduction** to enhance efficiency with larger datasets.

In conclusion, the system provides a solid foundation for personalized nutrition, helping users make healthier dietary choices based on their individual profiles.

Future Enhancements:

In the future, the diet recommendation system could be significantly enhanced by integrating **deep learning models**, such as **Convolutional Neural Networks (CNNs)** or **Recurrent Neural Networks (RNNs)**, to better capture complex nutritional patterns and user behavior over time. These models could handle high-dimensional data more efficiently and improve the accuracy of personalized recommendations. Additionally, **autoencoders** could be utilized for feature extraction and dimensionality reduction. Another key enhancement would be the integration of **real-time user feedback**. By incorporating reinforcement learning, the system could continuously adapt and refine its suggestions based on user responses to previous meals, creating a more dynamic and personalized experience. Furthermore, **Natural Language Processing (NLP)** could be leveraged to process user inputs in natural language, allowing the system to understand dietary preferences or restrictions expressed in free text and transform them into actionable data for personalized meal planning.

The system could also be expanded to include **multimodal data**, incorporating inputs from **biometric data** (e.g., weight, body mass index) or **wearable devices** (e.g., activity levels, sleep patterns). This would enable the system to make even more accurate and context-aware recommendations tailored to the user's health status. As the dataset grows, **Approximate Nearest Neighbor (ANN)** algorithms, such as **LSH (Locality-Sensitive Hashing)** or **HNSW (Hierarchical Navigable Small World)**, could be employed to scale the system, ensuring faster response times and maintaining high-quality recommendations despite large datasets. Additionally, **clustering techniques** like **K-Means** or **Hierarchical Clustering** could be used to group users based on similar dietary preferences, further improving the specificity of the recommendations. Lastly, integrating the system with **recipe databases** and **e-commerce platforms** could provide users with a seamless, end-to-end experience, enabling them to not only receive dietary suggestions but also easily purchase ingredients or meals online, enhancing convenience and accessibility.

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