

Food Recommendation Based on Health Issues and Climatic Conditions

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Abstract

In an era where health-conscious decision-making is becoming increasingly important, food choices play a crucial role in overall well-being. This paper presents a comprehensive review of food recommendation systems that integrate health conditions and climatic factors. By leveraging machine learning methodologies, particularly Random Forest (RF), the study explores how dietary suggestions can be tailored to individual health needs while considering seasonal variations. Various techniques, including classification algorithms and data-driven approaches, are analyzed to evaluate their efficiency in personalizing nutritional advice. Key studies are examined to compare the effectiveness of different models in providing accurate food recommendations. Additionally, prevailing challenges such as data imbalances and the dynamic nature of dietary preferences are discussed. This study underscores the significance of intelligent recommendation systems in fostering healthier eating habits and outlines future research directions aimed at enhancing their adaptability and precision.

Keywords: Random Forest (RF), One-hot Encoding, health, climatic conditions, machine learning

1. Introduction

Making well-informed decisions about diet and health is essential in today's busy world. The food we consume directly impacts our well-being, influencing energy levels, immunity, and overall health. However, dietary choices are often influenced by multiple factors, including personal health conditions and environmental conditions such as seasonal variations. As climate shifts impact food availability and nutritional requirements, there is a growing need for intelligent systems that provide tailored dietary recommendations.

This study introduces a comprehensive machine learning-based food recommendation system that customizes dietary suggestions based on two critical aspects: individual health conditions and climatic influences. The system consists of two primary components. The Health module analyzes user health conditions to provide scientifically backed nutritional recommendations, helping individuals choose foods that align with their medical needs. The Climate module further refines suggestions by accounting for seasonal and environmental conditions, ensuring dietary choices remain beneficial regardless of external changes.

By integrating machine learning algorithms, particularly Random Forest, the system offers an advanced solution for generating data-driven, personalized food recommendations. This project aims to bridge the

gap between nutritional science and artificial intelligence, providing users with an adaptable tool to make informed dietary choices.

Furthermore, the implementation of such a system has significant implications for individuals managing chronic illnesses such as diabetes, cardiovascular diseases, and food allergies

2. Literature Overview

The literature on food recommendation systems has significantly advanced with the integration of artificial intelligence and machine learning techniques. Several studies have explored different methodologies to improve recommendation accuracy by incorporating health conditions, climate variations, and user preferences.

Manasi Khadanga (2023) introduced a feedback-based food recommendation system utilizing hybrid deep learning. By combining Convolutional Neural Networks (CNNs) with sentiment analysis from user reviews, this model enhances recommendation precision and personalizes the user experience. The study highlights how hybrid deep learning surpasses traditional methods in identifying user preferences accurately.

Liuyi Chen (2023) conducted a survey on machine learning applications in weather forecasting, identifying AI-driven improvements in climate prediction accuracy. The study suggests that integrating AI methodologies into food recommendation systems can help align dietary choices with climate conditions, enhancing recommendation reliability.

Reema Golagana (2023) developed a machine learning-based diet recommendation system that classifies food items based on user health conditions. The study categorizes recommendations into weight loss, weight gain, and health maintenance, demonstrating AI's effectiveness in personalized diet planning.

Mary Divya Shamili (2022) explored AI's impact on food supply chain management and consumer nutrition. The study highlights AI's role in optimizing meal planning, reducing food waste, and improving dietary adherence, showcasing its benefits in modern food systems.

Abhaya Kumar Sahoo (2019) introduced DeepReco, a health recommender system utilizing deep learning and collaborative filtering. By analyzing health records and lifestyle patterns using RBM and CNNs, the model provides personalized dietary recommendations, emphasizing AI's potential in predictive healthcare.

Tossawat Mokdara (2022) proposed a deep neural network-based food recommendation system that predicts user food preferences by analyzing historical eating patterns. The study confirms that deep learning significantly enhances recommendation accuracy and personalization. These studies highlight advancements in AI-driven food recommendation systems.

By integrating climate data, health conditions, and user preferences, modern models provide precise, personalized dietary guidance. This research builds on these findings to develop a more adaptive and intelligent food recommendation framework.

Table 1: Comparison Table

Year	Author(s)	Proposed Work	Proposed Algorithm
2023	Manasi Khadanga	Feedback Based Food Recommendation System Using Hybrid Deep Learning	CNN
2023	Liuyi Chen	Machine Learning Methods in Weather and Climate Applications	ConvLSTM
2024	Mahmoud Y. Shams	Enhancing crop recommendation systems with explainable AI	Gaussian Naïve Bayes (GNB)
2019	Abhaya Kumar Sahoo	Deep Learning Based Health Recommender System Using Collaborative Filtering	Convolutional Neural Networks (CNN)
2024	Mehrab Mustafy Rahman	Agricultural Recommendation System based on Deep Learning	Bidirectional Long Short Term Memory
2023	Reema Golagana	Diet Recommendation System Using Machine Learning	Decision Tree
2022	Pragya Dwivedi	Food Recommendation System	KNN
2022	Tossawat Mokdara	Personalized Food Recommendation Using Deep Neural Network	CNN
2021	Ramesh Jain	Food Recommendation System	SVM
2020	Elakkiya & Dhandapani	Food Recommendation using Deep Learning.	CNN, LSTM
2021	Razali et al.	Multi-criteria Food Recommendation System	Collaborative Filtering, KNN
2024	Kaushal & Kumar	Health focused Food suggestion System	Neural Networks, Decision Trees
2023	Salehi et al.	Health-focused Food suggestion System	Neural Networks, Decision Trees & gradient Boosting

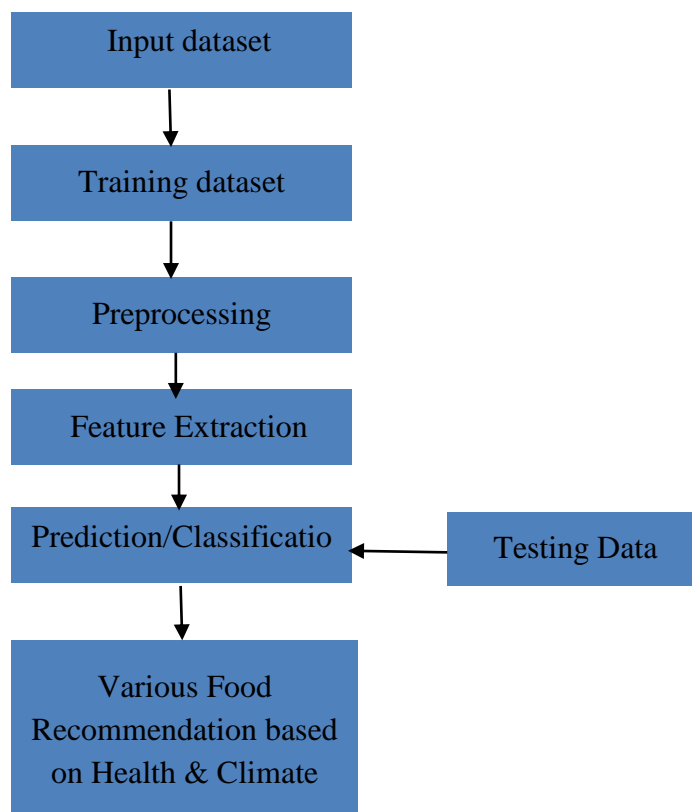
3. Methodologies and Approaches

To develop an efficient food recommendation system, multiple factors must be considered, including health constraints, environmental influences, and dietary preferences. The proposed system follows a

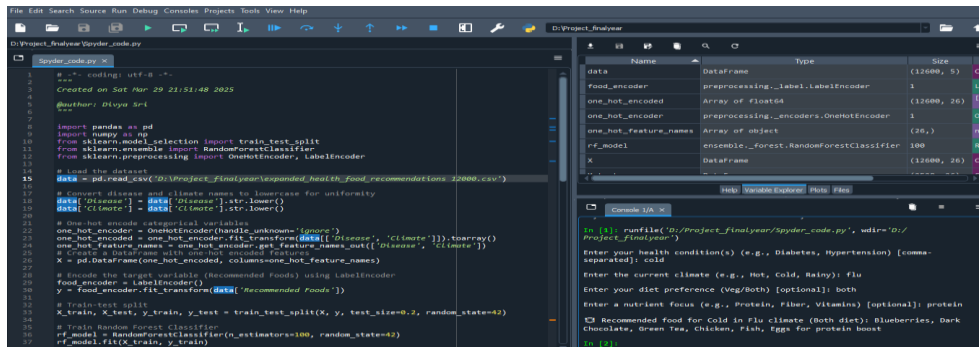
structured workflow, from data acquisition and preprocessing to model training and recommendation generation. The methodology ensures that the system delivers accurate and relevant food suggestions based on user-specific conditions and climatic factors. This project utilizes One-Hot Encoding for processing categorical data and the Random Forest algorithm for predictive analysis.

One-Hot Encoding: One-hot encoding is a preprocessing technique that transforms categorical variables into a numerical format that machine learning models can process effectively. It works by creating a binary vector for each category, where only one position is set to '1' while the rest are '0.' This method ensures that categorical values, such as different health conditions or climate types, are represented without implying any order or ranking among them. By eliminating the risk of misinterpretation caused by arbitrary numerical assignments, one-hot encoding helps machine learning algorithms recognize patterns more accurately and improves predictive performance across various applications.

Random Forest: Random Forest is a machine learning algorithm that enhances predictive accuracy by combining multiple decision trees into an ensemble. Each tree is trained on a randomly selected subset of the data, and the final prediction is determined by aggregating the outputs of all trees, reducing the likelihood of overfitting. This approach allows the model to handle complex relationships between variables effectively. When applied to one-hot encoded data, such as health conditions and climatic factors, Random Forest can analyze multiple features simultaneously to identify meaningful patterns. This makes it particularly useful for applications like food recommendation systems, where dietary suggestions need to be tailored based on both medical conditions and environmental factors.



This study employs One-Hot Encoding for preprocessing categorical data and utilizes a Random Forest Classifier to generate personalized food recommendations based on climatic and health conditions. The implementation is conducted in Python, using the Spyder IDE, to develop and test the predictive model. The core implementation is illustrated in Figure 1.



```
1 # -*- coding: utf-8 -*-
2 """
3 Created on Sat Mar 29 21:51:48 2025
4 @author: Divya Sri
5 """
6 import pandas as pd
7 from sklearn.preprocessing import LabelEncoder
8 from sklearn.model_selection import train_test_split
9 from sklearn.ensemble import RandomForestClassifier
10 from sklearn.preprocessing import OneHotEncoder, LabelEncoder
11
12 # Load the dataset
13 data = pd.read_csv("D:/Project_FinalYear/Expanded_Health_Food_Recommendations_20000.csv")
14
15 # Convert disease and climate names to lowercase for uniformity
16 data['Disease'] = data['Disease'].str.lower()
17 data['Climate'] = data['Climate'].str.lower()
18
19 # One-hot encode categorical variables
20 one_hot_encoder = OneHotEncoder(handle_unknown='ignore')
21 one_hot_encoded = one_hot_encoder.fit_transform(data[['Disease', 'Climate']]).toarray()
22 one_hot_feature_names = one_hot_encoder.get_feature_names_out(['Disease', 'Climate'])
23 # Create a DataFrame of one-hot encoded features
24 X = pd.DataFrame(one_hot_encoded, columns=one_hot_feature_names)
25
26 # Encode the target variable (Recommended Foods) using LabelEncoder
27 food_encoder = LabelEncoder()
28 y = food_encoder.fit_transform(data['Recommended Foods'])
29
30 # Train-test split
31 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
32
33 # Train Random Forest Classifier
34 rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
35 rf_model.fit(X_train, y_train)
```

Figure 1: Python Implementation of One-Hot Encoding and Random Forest Classifier.

This script preprocesses the dataset by converting categorical variables into numerical form using One-Hot Encoding. It then trains a Random Forest model to classify and recommend food items based on climate and health factors.

Implementation:

The system is developed in Python and follows a structured workflow:

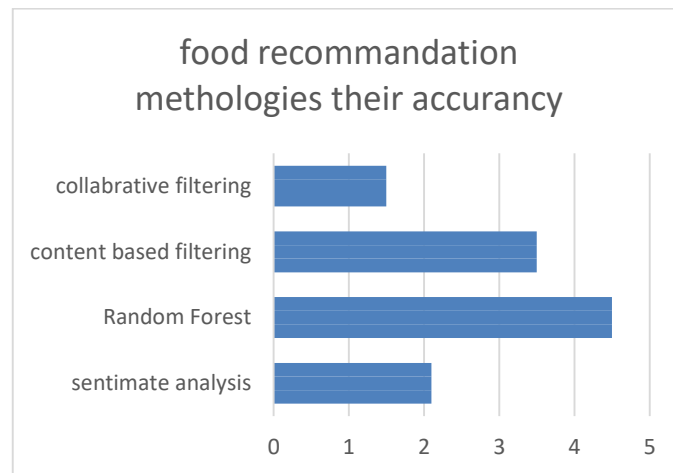
- Collecting user input regarding health conditions and climate.
- Standardizing disease and climate labels for consistency.
- Applying one-hot encoding to transform categorical variables.
- Training the Random Forest model to predict the most suitable food options.
- Generating personalized food recommendations based on user input.

4. Findings and Trends

A. Enhanced Personalization Through Machine Learning: Machine Learning (ML) enables personalized dietary recommendations by analyzing an individual's health conditions, allergies, and nutritional requirements. Unlike generic diet plans, ML-based systems continuously refine suggestions based on user feedback and real-time health data. This adaptive approach ensures that recommendations remain relevant and effective over time. By aligning meal choices with specific dietary needs, users can achieve better health outcomes.

B. Adaptability to Climate and Environmental Conditions: Nutritional needs vary with changing weather conditions, making climate-aware food recommendations essential. By incorporating seasonal and environmental factors, the system suggests foods that help maintain optimal health in different climates. For instance, hydrating fruits are recommended during hot summers, while nutrient-rich, warming foods are preferred in winter.

C. Data-Driven Decision Making for Better Nutrition: A data-driven approach enhances dietary planning by analyzing personal health records, food preferences, and environmental conditions. Unlike standardized nutrition guidelines, these recommendations are tailored to individual needs, improving their effectiveness. Real-time data analysis helps users make informed food choices that align with their health goals.



5. Challenges and Gaps

Accurate and diverse data sets are essential for refining the system's performance. Variability in dietary habits, climate conditions, and medical recommendations must be continuously accounted for. The integration of real-time climate updates presents a challenge in maintaining recommendation relevance, while optimizing model adaptability to diverse health conditions remains a key area of development.

6. Future Research Direction

A. Expanding Dataset and Diversity: Collecting a larger and more diverse dataset that includes a broader range of health conditions, dietary habits, and regional climate variations will enhance the accuracy and inclusivity of food recommendations. This will ensure the system accommodates personalized nutrition plans for diverse populations and different cultural food preferences.

B. Integration of Real-Time Data Sources: Incorporating real-time climate tracking, medical research updates, and regional dietary trends will help refine the model for context-aware and adaptive recommendations. Using API-based climate monitoring and medical literature updates can make the system more responsive to seasonal dietary requirements and emerging health research.

7. Result

The web-based Health Food Recommendation System is designed to assist users in selecting suitable food options based on their health conditions, climate preferences, and dietary choices. By leveraging a Random Forest machine learning model combined with One-Hot Encoding, the system predicts and suggests appropriate food items based on user inputs.

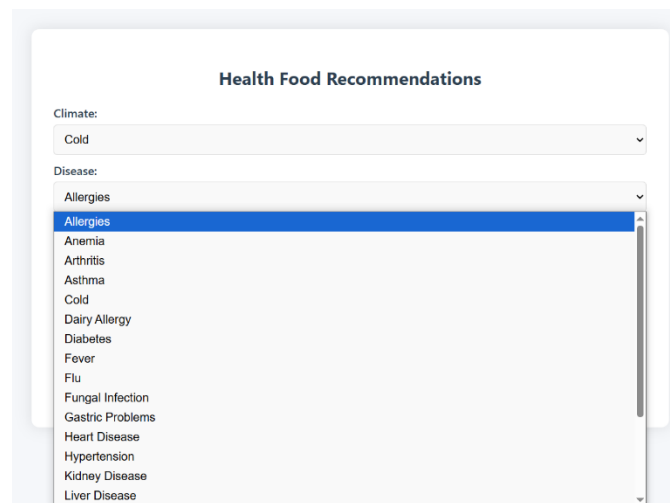


Figure 2: User selecting input parameters

In Figure 2, the interface allows users to choose parameters such as climate, medical condition, nutrient focus, and food preference through dropdown menus. Once the user clicks on the "Get Recommendations" button, the system processes these inputs to generate personalized food suggestions.



Figure 3: Recommended foods displayed after clicking "Get Recommendations"

Upon submission, the system presents a curated list of recommended foods tailored to the user's selections. As illustrated in Figure 3, when a user specifies Diabetes and chooses Fiber as the nutrient focus, the system suggests fiber-rich foods such as Oats, Lentils, Apples, Green Tea, and more.

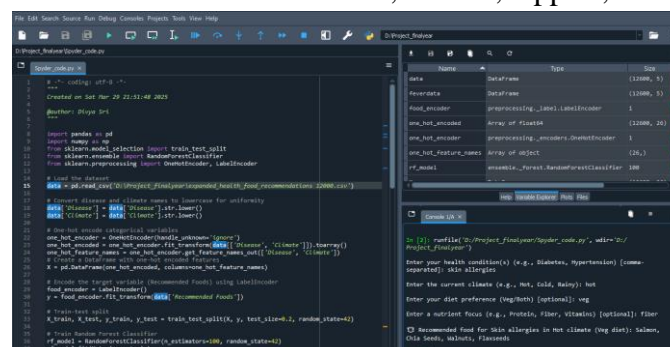


Figure 4: Console Output Displaying Food Recommendations.

The trained model processes user input—such as climatic conditions (e.g., humid, cold) and health conditions (e.g., diabetes, hypertension)—to generate personalized food recommendations. The console output showcasing the final recommendations is displayed in Figure 4. The program takes user inputs, applies the trained model, and returns relevant food recommendations. This demonstrates the successful implementation of the proposed system.

8. Conclusion

This project delivers a food recommendation system that considers health conditions and climatic variations, offering a valuable approach to personalized nutrition. By utilizing Machine Learning techniques such as One-Hot Encoding and the Random Forest algorithm, the system ensures accurate and tailored dietary suggestions based on individual health needs and environmental factors. The system's adaptability allows for continuous improvements by incorporating updated datasets and emerging health insights. By factoring in climatic variations, the recommendations help users make informed dietary choices suited to different weather conditions.

While the system establishes a strong foundation for personalized food recommendations, future enhancements could focus on expanding the dataset to include more diverse dietary options and improving personalization through user-specific health data. These advancements can further refine the system's effectiveness in promoting better nutrition and overall well-being. By helping individuals make health-conscious and climate-aware food choices, this system serves as an effective tool for promoting better nutrition and overall well-being. With continuous advancements, it has the potential to enhance dietary decision-making and support a more personalized approach to healthy eating.

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