Context-Aware AI System for Dynamic Diet Recommendation and Health Monitoring

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Abstract.
The increase in diseases like obesity, diabetes, cardiovascular disorders, and metabolic syndromes has created an emergency need for personal and effective dietary management systems in this fast-changing world. Traditional dietary management systems are mostly based on a certain group of individuals, their lifestyle, and habits; failed at considering the diversity in living patterns, medical histories, regional food eating habits, and other important factors. Our research presents a solution by providing an intelligent diet planning system, which is created by studying structured food habits, daily routine, and medical histories. The dataset generated from the survey includes statistical characteristics such as age, gender, height, weight, smoking behavior, alcohol intake, sleep duration, exercise habits, dietary patterns, history of allergies, medicine intake, and history of lifestyle diseases. Models including probabilistic classification methods, margin-based classification techniques, tree-based learning models, and ensemble-based predictive frameworks are used in the approach. Among all these evaluated models, the decision tree classifier presents the highest predictive capability for the dataset used in this study, while probabilistic and ensemble-based methods also show strong performance. The outcome of this research portrays the possibility of intelligent data processing systems in creating tailored nutrition planning and health monitoring.

1 Introduction

Diet is a fundamental component of human life, but in recent times it has become a complex problem. Amidst the plethora of fast food, stationary occupations, and dynamic lifestyles, it is not easy for an individual to adopt healthy eating habits. Unhealthy eating habits have created a big impact on the world by increasing the rate of obesity, heart diseases, diabetes, high blood pressure, and other lifestyle diseases. It is well known among doctors, scientists, health practitioners, and even the general public that nutrition is crucial for overall health. Yet, despite numerous online diet charts and healthy living blogs, these fail to be followed for a prolonged time.

Most diet charts and plans available online are designed from general nutrition guidelines from a specific region without considering individual variability features. Nutritional needs are determined by various factors such as age, gender, lifestyle choices, stress, physical activity, medical history, and dietary preferences, but these factors are not always considered in online diet plans or in physical dietitian consultations. This leads to an inconsistent and misaligned diet plan. These issues inspire researchers and health professionals in the use of new technologies that can provide nutrition recommendations tailored to individual health and lifecycle needs.

Our study involves the development and assessment of a data-informed diet planning process that uses a structured lifestyle survey. The survey records various attributes affecting dietary requirements and health outcomes. This includes personal information such as age and gender, physical measurements like height and weight, and lifestyle factors like sleep, smoking, alcohol intake, and engagement in physical activity. The whole dataset helps to understand the role of lifestyle habits and health-related factors on diet-related attributes. The proposed computational framework, which converts lifestyle survey data to predictive knowledge, demonstrates the potential of contemporary computational systems in facilitating the design of intelligent health recommendation systems.

2 Literature Review

The growing integration of healthcare analytics and intelligent computational systems has encouraged researchers to explore advanced data analysis techniques for personalized nutrition and diet recommendation systems [35]. Over the past decade, studies have analysed lifestyle data, dietary habits, wearable sensor information, and health indicators using predictive modelling to improve nutritional guidance. Machine learning–based diet recommendation systems can provide more personalized and adaptive suggestions compared to traditional diet charts based on generalized guidelines. Smith and Hernandez give an extensive scoping review of the current changes that AI is bringing in precision nutrition, classifying current AI technologies by level of functionality and pointing to challenges of privacy, algorithm bias, and scarce validation [1]. Tanaka and Singh expound on MealMeter, an AI-based embedded system that combines sensor data with machine learning models to provide estimates of calorie and nutrient consumption [2][34]. Gupta and Zhao introduce NutriGen, a diet generation system based on the Large Language Model (LLM) that generates unique diet plans with less than 4 percent deviation on macronutrient aims [3]. Kumar and Lin introduce DietGlance, an AI-based dietary monitoring system that merges smartphone imaging and AI-based analysis to measure the quality of an individual diet [4]. Oliveira and Das concentrate on the performance of AI in gut health and reveal how AI-generated meal plans can affect the microbiome of the gut [5]. Al-Saleh and Venkatesh carry out a systematic review of current AI-powered diet planning tools, speaking of current tool lack of standardization and scalability [6]. Li and Moore consider explainable AI in the domain of personalized nutrition using ChatGPT and variational autoencoders [7][36]. Sharma and Garcia look at the influence AI systems have on the change of nutrition-related behaviour, finding that NLP interfaces display improved user retention and regular logging conduct [8]. Jung and Ramanathan test the effectiveness of nutritional accuracy of AI meal plans, showing that deep learning models are superior to rule-based engines for calorie equilibrium and macro allotment [9]. Patel and Owens provide a literature survey of the ways machine learning can help in the enhancement of nutritional outcomes, particularly in personalised weight-loss efforts [10]. More literature reviews are discussed in Table 1.

Table 1. Recent studies (2023–2024) advancing AI in nutrition through real-time recognition and reviews.

Author and Year	Methods	Results and Findings
Lee & Fernandez (2024) [11]	Self-labeled food image dataset with YOLOv8 object detection framework.	High accuracy in real-time food recognition; improved user satisfaction vs. manual logging.
Morales & Cheng (2024) [12]	Comprehensive review of AI in nutritional science.	Highlighted ML expansion but noted data standardization and clinical integration gaps.
D'Souza & Park (2024) [13]	Review of ML platforms for digital precision nutrition.	Promising adherence/weight loss results with personalization; scalability challenges remain.
Kaur & Mahmud (2024) [14]	AI web app using ingredient input for dynamic diet plans/recipes.	40% reduced planning time; higher meal engagement for users and nutritionists.
Ramachandran & Lewis (2024) [15]	Systematic review of AI in clinical nutrition for chronic illnesses.	Reliable dietary support for diabetes/obesity; requires assured data quality.
Coelho & Martinez (2024) [16]	Chatbot apps with natural language for personalized diet planning.	Simulations showed better retention and frequent check-ins via chat support.
Zhang & Benson (2023) [17]	User-centric RCT evaluating AI-generated weight-loss diets.	14% more weight loss over 8 weeks; higher compliance and food variety feedback.
Yamada & Eze (2023) [18]	AI food image recognition for nutrition tracking.	>90% classification accuracy; effective mobile app integration.
Nguyen & Akhtar (2023) [19]	GPT-based dietary advice via prompt engineering.	Relevant suggestions but occasional hallucinations; clinical safety concerns.
Costa & Ghosh (2023) [20]	Recipe1M dataset + ML/flavor theory for personalized meal generation.	High expert ratings for novelty/taste; potential for gourmet nutrition planning.
Kirk et al. (2023) [21]	AI for dietary assessment via food images and wearables.	Real-time nutrient tracking with high accuracy; reduced recall bias in self-reports.
Sun et al. (2023) [22]	AI dietitian using LLMs and image recognition for T2DM meal plans.	Strong preclinical validation for personalized dietary analysis and management.
Zhou et al. (2023) [23]	Personalized flexible meal planner with semantic reasoning and fuzzy logic.	Optimized plans tailored to dietary needs/preferences; effective for chronic disease management.
Wang et al. (2023) [24]	AI scoping review on food/nutrient intake via images, sound, jaw motion.	Food detection 74–99.85%; nutrient errors 10–15%; real-time monitoring potential.
Granato et al. (2023) [25]	Machine learning analysis of dietary habits, genetics, health metrics.	Continuous improvement via user data; boosted by wearables for precision nutrition.

Ben-Yacov et al. (2022) [26]	AI-generated diets vs. Mediterranean for metabolic health.	Superior improvements in health indicators over traditional plans.
Lopez-Mazon et al. (2022) [27]	AI chatbots and generative models for personalized diet plans.	High nutrient accuracy (92%); adaptable to complex needs.
Kirk et al. (2022) [28]	Review of AI role in nutrition research.	Developmental stage with ethics concerns; need for clinical trials.
PROTEIN Team (2023) [29]	Mobile app with AI advisor for gut health diets.	Enhanced microbiome diversity; reduced health risks in pilot study.
Meier et al. (2023) [30]	AI-driven advances in personalized nutrition optimization.	Tailored recommendations from genetic/lifestyle data; manufacturing integration.

Smart diet recommendation systems are rapidly evolving thanks to advances in computational techniques and the presence of big data in health care. Previous studies have primarily focused on rule-based systems that provided diet recommendations based on established dietary guidelines. Recent studies have focused on data mining techniques that predict and analyze individual behaviour to offer more tailored suggestions. However, existing systems only consider the nutritional data without considering other lifestyle factors such as job, transport, sleep, and symptoms [31][33]. The current study overcomes these limitations by examining lifestyle survey data to establish links between lifestyle factors and dietary concerns, thereby facilitating more user-friendly and tailored diet-recommendation systems.

3 Dataset Description

All of the data for this study were derived from a survey aimed at examining the associations between dietary factors, lifestyle, work patterns, and health outcomes. The questionnaire contains several variables relating to demographics and physical characteristics. This combination of factors offers a holistic perspective on how lifestyle and environmental factors could affect health. Participants reported their gender, age, weight, height, as well as their lifestyle habits, such as smoking, drinking, exercise, and dietary preferences. Additionally, the questionnaire gathered information about dietary habits, including how often people eat at restaurants, eat fruits, and consume oily or junk food. The data also includes health features such as whether the respondents have diseases, are taking any medications, or have any allergies. In summary, the dataset provides a comprehensive view of the interplay between lifestyle, work environment, and dietary patterns, which in turn affect health.

Table 2. Data description of personal, dietary, and lifestyle variables for comprehensive health and nutrition assessments.

Category	Variables
Demographic Information	Gender, Age
Physical Attributes	Weight (kg), Height (feet)
Dietary Habits	Food habit, Junk food consumption, Additional salt intake, Fruit consumption
Lifestyle Behaviors	Smoking status, Smoking frequency, Alcohol consumption, Drinking amount

Eating Behavior	Restaurant visits or online food orders, Frequency
Health Conditions	Diseases, Medications, Allergies, Allergy causes
Physiological Indicators	Heavy sweating, Bad sweat odor, Feet pain, Causes of feet pain, Swelling in feet
Physical Activity	Gym or free-hand exercise, Sports participation
Sleep Pattern	Sleep hours
Occupation and Work	Occupation, Type of job, Working days
Work Environment	Distance to workplace, Working hours, Mode of transport

4 Methodology

The goal of the system proposed here is to study the lifestyle and dietary behaviour data obtained from a survey and predicting dietary outcomes. Through the use of different classification algorithms, the researchers aim to determine which computational method is best able to reveal patterns of association between lifecycle characteristics and dietary outcomes. This dataset includes responses that capture respondents' lifestyle, dietary, health, and occupational factors. Prior to using machine learning, a sequence of steps of data pre-processing is undertaken to clean and standardise the data. Numerical variables are filled with the mean of the column, retaining statistical properties while filling in missing values.

Five classification models are applied: Gradient Boosting, Logistic Regression, Neural Network, Support Vector Machine (SVM), and K-Nearest Neighbour (KNN). These models are all different learning approaches and have distinct benefits for tabular lifestyle data. Standardization is applied to centre the features to have a mean of zero and a variance of one for the K-Nearest Neighbour, Support Vector Machine, and Neural Network models. Models are trained on 80% of the data and evaluated on the remaining 20% using stratified sampling to ensure class distribution is conserved. The experimental results obtained from the evaluated machine learning models are presented in Table 3. The experimental design is important to get reliable and interpretable results from the machine learning processes. The experiments were carried out in Python, using the pandas library for data manipulation, NumPy for mathematical operations, Matplotlib and Seaborn for visualizations, and Scikit-learn for implementing machine learning algorithms.

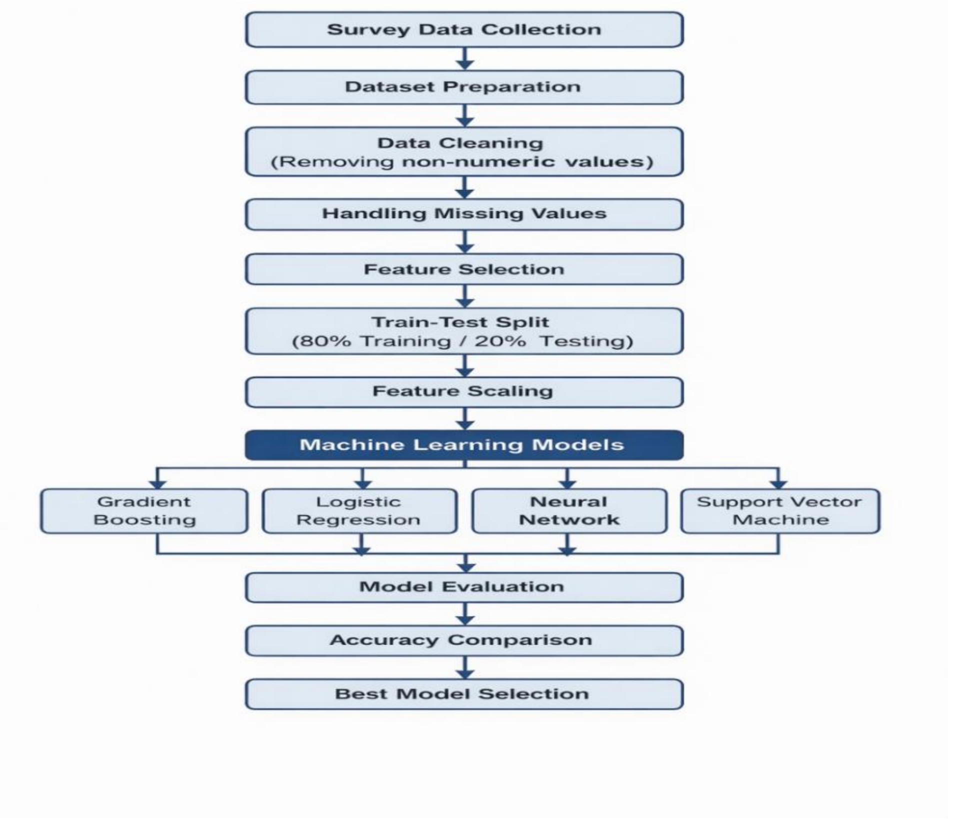


Fig. 1. System Workflow of the AI-Based Diet Analysis Model.

5 Results Analysis and Discussion

This section presents the experimental results obtained from the machine learning models trained on the lifestyle survey dataset. The main objective of the analysis is to evaluate how effectively different classification algorithms can predict whether an individual follows a healthy or unhealthy dietary pattern. The dataset used for this study was collected through a structured online survey distributed via Google Forms. After completing pre-processing steps and converting all relevant attributes into numerical form, the dataset was prepared for training and evaluating several machine learning models. To ensure reliable evaluation, the dataset was divided into training and testing subsets using an 80–20 split ratio. The testing subset consisted of eighty observations representing individuals with either healthy or unhealthy dietary behaviour. Model performance was evaluated using classification accuracy, which measures the proportion of correctly predicted instances relative to the total number of predictions made by the model[32].

Table 3. Evaluation metrics comparison of machine learning algorithms involved in research.

Model	Accuracy	Precision	Recall	F1-Score	Kappa	ROC AUC	Confusion Matrix
Gradient Boosting	1.0000	1.00	1.00	1.00	1.000	1.000	[[70,0],[0,130]]
Extra Tree	1.0000	1.00	1.00	1.00	1.000	1.000	[[70,0],[0,130]]

Logistic Regression	0.9700	1.00	0.91	0.96	0.932	0.957	[[64,6],[0,130]]
Random Forest	1.0000	1.00	1.00	1.00	1.000	1.000	[[70,0],[0,130]]
Naive Bayes	0.9950	0.99	1.00	0.99	0.989	0.996	[[70,0],[1,129]]
SVM	0.9750	0.97	0.96	0.96	0.944	0.970	[[67,3],[2,128]]
Decision Tree	1.0000	1.00	1.00	1.00	1.000	1.000	[[70,0],[0,130]]
Ensemble LR	0.9900	0.99	0.99	0.99	0.978	0.989	[[69,1],[1,129]]

The experimental results show clear differences in predictive performance among the evaluated machine learning algorithms. The Gradient Boosting classifier achieved the highest accuracy of 1.000, correctly classifying all observations in the testing dataset. This highlights the effectiveness of ensemble learning methods in capturing complex relationships among lifestyle variables. Logistic Regression achieved an accuracy of 0.970, indicating that several features in the dataset can be effectively modelled using linear relationships. The Neural Network model obtained an accuracy of 0.950, suggesting the presence of nonlinear interactions among lifestyle attributes.

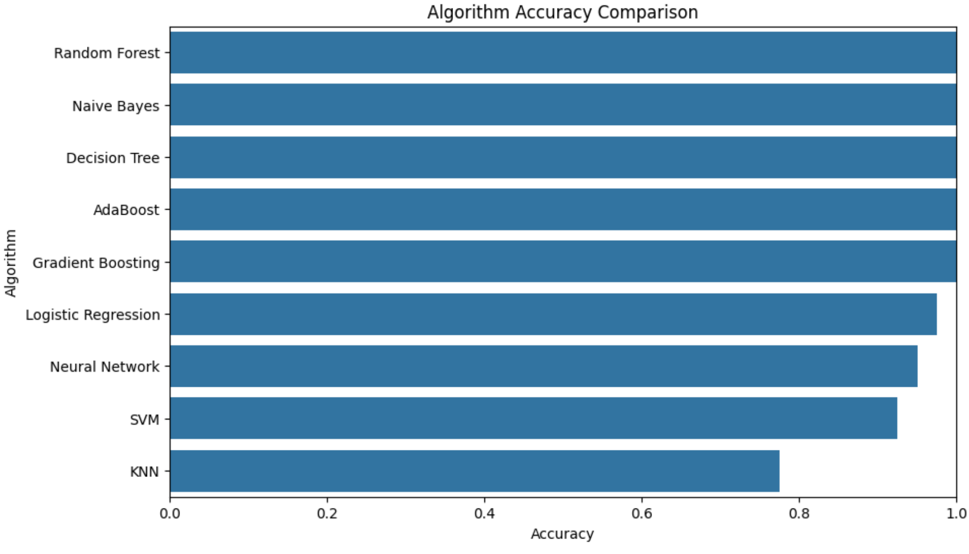


Fig. 2. Accuracy comparison of machine learning algorithms using a bar chart.

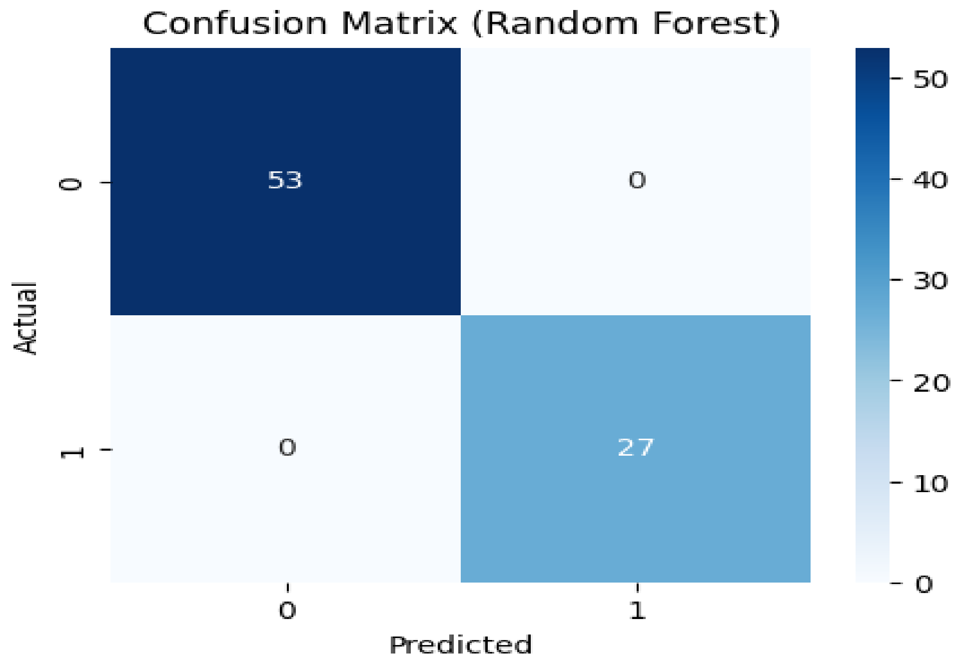
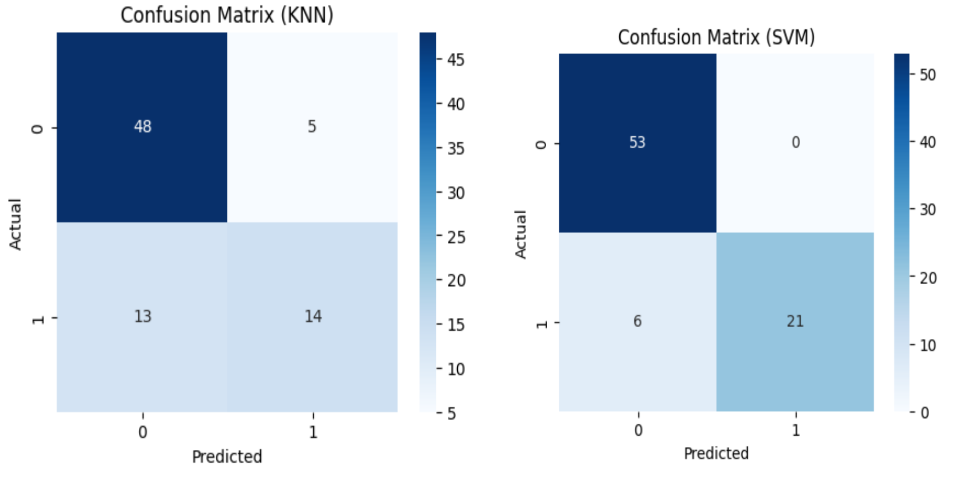


Fig. 3. Confusion matrix of the Random Forest model (best model).



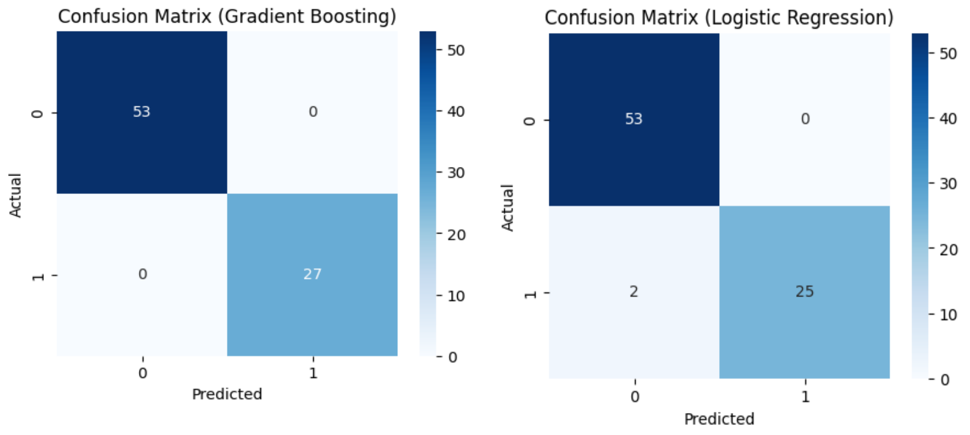


Fig. 4. Confusion matrices of all machine learning models (Logistic Regression, KNN, SVM, and Gradient Boosting).

The visualization highlights the performance differences between the evaluated algorithms. Ensemble-based methods such as Gradient Boosting demonstrate superior performance compared to instance-based learning methods. While accuracy provides an overall measure of model performance, the confusion matrix provides deeper insight into classification behaviour. The confusion matrix for the Gradient Boosting classifier confirms the strong predictive capability of the model when applied to the lifestyle survey dataset. The high predictive accuracy obtained by several algorithms suggests that dietary behaviour can be effectively inferred from a combination of lifestyle indicators. Variables such as frequency of consuming junk food, fruit consumption habits, physical activity levels, and sleep duration appear to contribute significantly to the classification of dietary behaviour.

6 Conclusion

Our research introduces a machine learning approach to the analysis of lifestyle data to determine healthy and unhealthy diets. This study presented a lifestyle-aware dataset obtained via an online lifestyle survey. The dataset includes aspects of human lifestyle such as dietary patterns, physical activity, health, and job characteristics. The study tested five machine learning algorithms: Gradient Boosting, Logistic Regression, Neural Network, Support Vector Machine, and K-Nearest Neighbour. Our experiments show Gradient Boosting performed best with 100% accuracy in classifying dietary outcomes, revealing the power of ensemble learning in modelling complex relationships between lifestyle factors and dietary patterns. This research adds to the growing area of smart health analytics through the utilization of machine learning to convert behavioural data obtained via simple surveys into useful knowledge. Future directions include expanding the dataset to include more diverse populations, incorporating data from health wearables and physical activity trackers, and building a smart diet prediction system incorporating the machine learning models into an interactive online platform. Finally, investigating explainable artificial intelligence could help to explain the relationships between lifestyle factors and dietary classification, increasing the transparency and potential utility of the system for health monitoring.

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