

Food Diet Recommendation System Using AI

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Abstract

This collection of scholarly papers reviews diverse interventions for dietary and health management, employing methodologies ranging from technology-driven systems to clinical and policy-based research. Several studies focus on integrating artificial intelligence (AI) and machine learning (ML) to deliver personalized dietary recommendations. One notable study described the “Diet Engine” system, which achieved 86% accuracy in food identification using image recognition and a deep learning network with 295 layers. It also reported that the Extra Tree Classifier reached 99% accuracy in predicting diet plans. Another study applied the K-means clustering algorithm to group users for personalized dietary planning, obtaining 96% accuracy. Clinical studies explored dietary interventions in specific populations. For example, one investigation tested the MIND diet on individuals with multiple sclerosis and found increased antioxidant status and weight loss in females. Another clinical trial targeting participants with cardiovascular disease reported modest improvements in diet quality after intervention-based education, although lifestyle modifications did not significantly change cardiovascular risk factors. A related study confirmed the feasibility of low-energy diets for individuals with obesity and chronic kidney disease, showing notable reductions in both weight and blood pressure. Beyond individual health, broader socioeconomic and environmental concerns were also addressed. One policy-focused paper examined the “affordability gap” of nutritionally adequate diets across countries such as the Dominican Republic, Ethiopia, and Indonesia, recommending this metric to guide social assistance and nutrition programs. Another study raised concerns about the health risks associated with plastic additives in food, emphasizing that infants are particularly vulnerable due to exposure levels exceeding safety thresholds. Finally, an analysis of diet and lifestyle mobile applications found that many incorporated behavior change techniques correlated with app quality. However, the review found limited scientific validation and a lack of safety features in most applications, underscoring the need for more evidence-based, user-protective digital health tools.

Keywords: *Artificial Intelligence (AI); Machine Learning (ML); K-means Clustering; Extra Tree Classifier; Social Assistance Programs; Plastic Additives; Food Safety; Behavior Change Techniques.*

1. Introduction

Today's society faces increasing health and nutritional challenges, reflected in the rising prevalence of chronic diseases such as obesity and diabetes, largely resulting from poor dietary habits and sedentary lifestyles. Conventional dietary guidelines often fail to produce effective outcomes because they overlook individual differences in genetics, health conditions, and personal preferences. This limitation underscores the growing need for personalized solutions in health and nutrition management.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have enabled the development of intelligent systems that provide personalized dietary recommendations. These technologies integrate various data sources, including user habits, medical history, and wearable device data into complex analytical models that generate tailored nutrition guidance. Emerging mobile applications and online platforms are making these solutions more user-friendly, precise, and accessible to the public.

Beyond improving individual diet quality and health outcomes, such innovations also address broader public health concerns. Research highlights two critical issues: the “food affordability gap,” which limits access to nutritious diets across many populations, and the growing exposure to plastic additives in food supplies, which pose additional health risks. Together, these challenges demonstrate the

multidimensional nature of modern public health issues and the vital role that AI-driven nutrition technologies can play in addressing them [1–3].

2. Research Methodology

This study employs a structured research methodology designed to analyze and compare artificial intelligence (AI) and machine learning (ML) models used in personalized dietary recommendation systems. The goal is to understand how these algorithms can improve accuracy, accessibility, and personalization in nutrition planning. The methodology has been described in sufficient detail to allow other researchers to replicate the approach and reproduce the findings.

1. Research Design

The study follows a systematic literature-based research design that combines qualitative synthesis with quantitative comparison. Fifteen scholarly papers published between 2022 and 2025 were reviewed to evaluate various algorithmic models and dietary intervention frameworks. Each paper was analyzed for its dataset characteristics, algorithm types, population size, and reported accuracy.

2. Data Collection

All studies were collected from reputable scientific databases such as ScienceDirect, IEEE Xplore, SpringerLink, and PubMed. The inclusion criteria focused on research addressing AI or ML in dietary planning, health management, and nutrition optimization. Studies such as Saad et al. (2025) [14] on the Diet Engine model, Shah et al. (2022) on the Extra Tree Classifier [15], and Waghela et al. (2025) [16] on K-means Clustering were included due to their high accuracy in predicting and classifying dietary patterns.

3. Analytical Framework

The analytical phase involved comparing the performance of ML models, including Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Decision Trees, and K-means Clustering. Accuracy, precision, recall, and F1-score were used as the primary evaluation metrics. Previously published models were referenced appropriately [4], and only modifications or performance insights specific to this review were emphasized.

4. System Workflow

The research also conceptualizes a generalized AI-based dietary recommendation workflow, comprising four primary stages:

1. Data Acquisition: Collecting user input such as age, gender, BMI, and dietary goals.
2. Preprocessing: Cleaning and structuring data for algorithmic analysis.
3. Model Application: Using ML algorithms to classify food images, cluster dietary preferences, and predict suitable diet plans.
4. Feedback and Optimization: Incorporating user feedback to improve the accuracy and adaptability of future recommendations.

5. Ethical Considerations

Since dietary recommendation systems rely on personal health data, privacy and confidentiality are essential. This research emphasizes compliance with data protection standards such as GDPR and HIPAA, ensuring that personal health information remains secure. Algorithmic fairness and data transparency were also considered to minimize bias in recommendations.

I. Theory and Calculation

• Theoretical Framework

The theoretical framework for this research is rooted in the integration of AI and ML methodologies to improve personalized nutrition and dietary recommendations. This system depends on the very fundamental principle that the dietary needs of every individual differ due to physiological variations in genetics and behavior. Conventionally designed population-based dietary recommendations often cannot capture individual differences and therefore require adaptive computational models that can process diverse, dynamic data inputs.

The main theory behind this study is predictive modeling through the use of machine learning classifiers and clustering algorithms, which work under the assumption that food preference, nutrient needs, and health outcomes can be predicted and optimized by data-driven learning mechanisms. AI models leverage user-specific parameters, such as Body Mass Index (BMI), caloric requirement, and macronutrient balance, to build customized meal recommendations.

The algorithms reviewed included Supervised Learning Algorithms, such as the Extra Tree Classifier [3], which had an accuracy of 99% in predicting diet plans, while Unsupervised Learning Methods such as K-means Clustering [13] have successfully grouped users based on similar nutrition and lifestyle characteristics with 96% accuracy. These findings support the theoretical assumption that algorithmic classification and clustering can more efficiently simulate human decision-making in nutrition planning compared to conventional methods.

• Calculation and Model Implementation

A practical implementation of this theory thus involves data-driven modeling and computation based on dietary and health-related datasets. The procedure starts with taking input parameters from a user, such as age, gender, height, weight, and activity level, to compute BMI and hence estimate caloric needs. The standard equation for calculating BMI is:

$$\text{BMI} = \text{Weight (kg)} / [\text{Height (m)}]^2$$

The calculated BMI now serves as an input parameter for classification models, which categorize users into one of the following categories: "Underweight," "Normal," "Overweight," or "Obese." Based on this categorization, a machine learning model predicts an appropriate diet plan. Food classification in systems such as the Diet Engine [15] relies on CNNs through the use of the YOLOv8 deep learning framework. Up to 295 hidden layers are used by this network to ultimately detect and classify food images with a reported

86% accuracy in its classification. Mathematically, CNN-based prediction is based on the convolution operation:

$$S(i,j)=(I*K)(i,j) = \sum_n \sum_l I(i-m,j-n)K(m,n)$$

6. Results and Discussion

The results of this study indicate the further and more trustworthy use of AI and ML algorithms in creating the right and personalized dietary recommendation systems. The comparative review and analytical synthesis indicate that the merging of data-driven models with nutritional science can significantly enhance dietary precision, health outcomes, and access.

1. Performance and Accuracy: Out of all the models examined, the Extra Tree Classifier presented the best performance with an accuracy of 99% in predicting suitable diet plans based on user history and preferences [3]. The K-means Clustering algorithm also managed to classify users into nutrition groups with 96% accuracy [13]. Therefore, it can be said that both supervised and unsupervised learning methods can model the dietary requirements effectively without major prediction errors. The Diet Engine with a 295-layer YOLOv8 CNN showed an 86% accuracy in food image classification and a detection precision of 96.5% for clear images [15]. These systems are proven to be better than conventional recommendation methods involving rule-based or static databases alone. The high classification accuracy of modern AI-based systems corroborates the strength of deep learning frameworks in handling complex, multi-dimensional dietary information.

2. Interpretation of Findings: The outcome of the study proves that AI diet systems can understand and adapt to individual dietary habits and nutrition needs more quickly than the conventional health counseling method. This conclusion agrees with Chiu et al. (2025) who introduced the Personal Health Support Model (PHSM) demo that. Nevertheless, not all problems have been solved and some challenges still exist. The researchers Pavlicek and Craddock (2025) concluded that the majority of the diet apps available in the market still have not been validated scientifically and their safety features are inadequate [14]. This finding points out that the area of algorithmic innovation is moving very fast, although its application in consumer products that are safe and evidence-based has not yet reached its final stage.

3. Wider Public Health Impact: AI-fuelled nutrition tools come to be seen as a part of the solution not only for individuals but also for solving the nutrition problems of the system as a whole. The “food affordability gap” is highlighted by Balagamwala et al. (2024), the lower access to nutrient-rich diets in poorer households, etc. [11]. With AI, this gap could be closed by giving recommendations of meal options that are not only nutritious but also local and cheap. At the same time, the work by Fernández-Arribas et al. (2025) about plastic additives in food reveals the necessity of coupling AI-based dietary guidelines with health risk monitoring tools [10].

4. Importance and Future Perspective: The combination of the overall results confirms the notion that AI adoption in dietary recommendations has the potential to offer personalised nutrition counselling with great efficiency, precision, and reach. The systems are quicker, rich in data, and flexible with respect to changes in health input, as compared to traditional interventions. The study advises that future progress should be directed towards the issues of

data openness, algorithmic equity, and unification with wearable health devices to further increase usability and reliability.

7. Conclusion

According to the research presented in the current issue, a higher-protein diet and moderate resistance training seem to be well-tolerated and did not adversely affect oxidative stress (OS) in older populations. It is noteworthy that the dietary intervention was participants' quoted diet may differ for each situation, condition and study design in this area with mixed results. For patients with cardiovascular disease attempting to eat a pretty healthy diet, after dietary counseling over 6 months, patients improved slightly in diet quality, but no significant changes were made in any cardiovascular disease risk factor. Conversely, and for adults with chronic kidney disease, a professional supervised low-energy diet fell into the "safe and effective" category under outpatient conditions for weight loss. The effects of a MIND diet intervention for participants with multiple sclerosis had positive effects on antioxidant defense systems and resulted in statistically significant weight loss among women in the study. Regarding technology, the applications of AI and machine learning tools are demonstrating strength to revolutionize personalized dietary or nutrition guidance. For example, the use of the Extra Tree classifier model type using advanced algorithms have achieved accuracy of 99% for dietary recommendations. Nevertheless, obstacles still exist regarding app development, with lots of popular diet apps lacking an evidence-based approach and safety features even though they have lots of behavior change techniques. On a larger scale, an important economic consideration is the "affordability gap" for healthy diets, which is a pressing global issue and policies such as social assistance (or food fortification) are important in addressing this. Lastly, an emerging public health concerns plastics and additives in food. Studies show plastic exposure may exceed safety thresholds, particularly in infants.

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