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Personalized Nutrition Recommendation System Based on Artificial Intelligence and Federated Learning

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Abstract: This study developed a personalized nutrition recommendation system based on federated learning and multiple sources of health data, including clinical records, genetic information, lifestyle surveys, and physiological data from wearable devices. The system was designed to provide individual dietary advice while protecting user privacy. A six-month controlled study compared the outcomes of a personalized intervention group with those of a control group following standard dietary guidelines. Results showed that the personalized group achieved a 15% increase in dietary quality scores, along with better health outcomes. These included an average weight loss of 3.0kg, a 2.0% reduction in body fat, and higher rates of normal blood pressure and stable blood glucose levels. In addition, 80% of participants in the personalized group reported higher satisfaction, noting that the recommendations matched their preferences and were easier to follow. The system also included methods to explain how each recommendation was generated, helping users and health professionals better understand and trust the results. Overall, this approach shows promise for improving nutrition management and supporting long-term health.

Keywords: personalized nutrition; federated learning; multimodal health data; dietary intervention; health monitoring

1. Introduction

Chronic diseases are a major global health concern. Recent studies indicate that by 2024, more than 68% of adults will have at least one chronic condition [1]. Research has consistently shown a strong link between unhealthy diets and chronic diseases [2,3]. For instance, a 2023 multinational study published in The Lancet Public Health reported that high sugar, high fat and high salt diets significantly increase the risk of cardiovascular diseases, diabetes and obesity [4]. In 2022 alone, poor diet contributed to 9 million cardiovascular-related deaths and 450 million diabetes cases worldwide [5]. Prolonged unbalanced eating habits not only disrupt metabolic functions but also greatly increase the risk of chronic diseases [6]. In contrast, a well-structured diet plays a vital role in disease prevention, improving quality of life and enhancing productivity, benefiting both personal health and professional performance [7]. As public awareness of health grows, the demand for customized health solutions has risen. A survey on urban health awareness in China found that 88% of respondents actively monitor their health and seek personalized dietary recommendations [8]. Traditional general nutrition guidelines are no longer sufficient. Different individuals have unique nutritional needs — for example, office workers with sedentary lifestyles and high stress levels may require specific dietary adjustments, while older adults may need easily digestible and nutrient-rich foods [9]. The increasing need for tailored nutrition plans has exposed the limitations of conventional advisory systems.

Artificial intelligence and machine learning have driven significant advancements in healthcare [10]. In medical imaging, deep learning algorithms now achieve over 92% accuracy in diagnosing chest X-rays. In treatment planning, machine learning helps predict patient responses to chemotherapy, improving success rates by 15-20%. However, in nutrition science, traditional centralized data processing faces major challenges. Health data comes from multiple sources and is often highly complex [11]. Wearable devices generate vast amounts of real-time physiological data, medical institutions maintain extensive health records and genetic testing labs provide intricate genomic data [12]. Additionally, individual eating habits and lifestyle choices add further complexity, making traditional data processing inefficient [13]. A significant drawback of centralized data storage and analysis is the high risk of data breaches, which can lead to severe privacy violations [14]. Federated learning, a decentralized machine learning approach, provides an effective solution by enabling collaborative model training across multiple organizations without sharing raw data, thus ensuring data security and privacy. Meanwhile, Transformer-based deep neural networks, known for their self-attention mechanisms, excel in processing complex sequential data, making them ideal for analyzing dietary patterns [15]. Additionally, reinforcement learning algorithms can dynamically adjust dietary recommendations based on real-time health status and user feedback.

This study integrates these advanced technologies to develop a highly efficient, privacy-secure, and interpretable personalized nutrition recommendation system. By addressing the gaps in current nutrition advisory models, this research meets the growing demand for personalized nutrition plans, offering a practical approach to improving public health.

2. Method

2.1. System Framework

The personalized nutrition recommendation system developed in this study integrates multi-source data collection, federated learning, AI-based analysis and explainable recommendations [16]. The data collection module gathers real-time data from wearable devices, electronic health records, genetic testing results and user lifestyle surveys, creating a detailed and individualized health profile [17]. The federated learning module, which serves as the system's core, allows for privacy-preserving collaborative learning. Each data provider processes and trains models locally, transmitting encrypted model parameters to a central server instead of raw data. The server aggregates these parameters, updates the global model, and then redistributes the improved model to all participants. This approach ensures secure multi-source data integration while safeguarding user privacy.

2.2. Data Processing and Algorithm Integration

During data preprocessing, redundant, inaccurate, and incomplete data are identified and corrected. Missing values are filled based on data type, and numerical data is normalized to a 0–1 range to maintain consistency across different features. Text-based data, such as dietary habits and lifestyle details, is converted into numerical representations using natural language processing (NLP) techniques. For AI-driven analysis, a Transformer-based deep learning model captures complex patterns between eating behaviors and nutrient intake [18]. At the same time, reinforcement learning dynamically adjusts dietary recommendations based on user feedback and evolving health conditions

[19]. Traditional machine learning models serve as auxiliary validation tools, further improving the accuracy and reliability of the recommendations through multi-algorithm collaboration.

2.3. Enhancing Explainability

To improve transparency and user trust, the system employs Local Interpretable Model-Agnostic Explanations (LIME) to assess the impact of individual input features on recommendations. Additionally, SHAP values are used to rank the importance of various factors influencing dietary suggestions, while decision tree models extract interpretable decision rules that clarify the system's reasoning [20]. Furthermore, visualization techniques such as heatmaps and interactive graphs provide clear and intuitive insights into how the system generates recommendations, helping both users and nutritionists understand and apply the personalized dietary advice more effectively.

3. Experimental Design, Data Collection, and Preprocessing

To evaluate the effectiveness of the AI and federated learning-based personalized nutrition recommendation system, this study conducted a structured experimental analysis. The data collection phase involved gathering comprehensive multi-source information, ensuring a broad and diverse dataset for validation.

3.1. Data Collection

A multimodal health dataset was developed through partnerships with certified hospitals, genetic testing agencies and wearable device programs [21]. It comprises 5,000 electronic health records (EHRs), including demographic details (age, sex, height, weight), medical history (chronic diseases, allergies, prior diagnoses) and clinical indicators such as blood test results, biochemical markers and body fat percentage [22]. Additionally, 1,000 genetic profiles focusing on loci related to nutrient metabolism and disease risk were collected. Physiological and behavioral data from 2000 participants were continuously recorded over three months using wearable devices, capturing step count, exercise duration, activity types, heart rate, blood pressure variability, and sleep quality. Dietary intake and lifestyle factors were assessed via structured online surveys and mobile tracking tools, documenting food choices, eating patterns, work-rest schedules, smoking, and alcohol use [23]. The resulting dataset supports individualized health analysis and risk prediction

3.2. Data Preprocessing

Data preprocessing was conducted to ensure quality, consistency, and analytical readiness. The panda's library in Python was utilized for data cleaning, including the removal of duplicates and erroneous entries. Numerical features were standardized to a 0–1 range to maintain uniformity across variables. Genetic information was encoded into categorical formats to support integration with clinical and lifestyle data. For unstructured text fields related to dietary habits and lifestyle descriptions, natural language processing (NLP) techniques — particularly word embedding — were applied to convert free-text responses into structured numerical representations. Following validation and transformation procedures, a high-quality, well-structured dataset was generated to support downstream model development and evaluation.

3.3. Experimental Design

A comparative study was conducted by dividing participants into an experimental group and a control group. The experimental group received personalized dietary recommendations generated by an AI-driven federated learning system, while the control group adhered to standardized, non-personalized dietary guidelines. Key health indicators — including body weight, body fat percentage, blood pressure and blood glucose levels —

were monitored at regular intervals over a six-month intervention period. To evaluate dietary effectiveness, a scoring system was developed to quantify food diversity and nutrient balance. Certified nutritionists independently reviewed participants' dietary logs and assigned scores based on nutritional quality and adherence to recommended intake levels [24]. In addition, user feedback was collected through structured surveys to assess satisfaction with the personalized recommendations and to evaluate the system's usability and acceptance in practical settings.

4. Experimental Results

4.1. Comparative Outcomes Between Intervention and Control Groups

After six months of intervention, the AI-driven personalized nutrition recommendation system based on federated learning yielded notable improvements over conventional dietary plans. Compared to the control group, which followed standardized guidelines, the experimental group achieved a 15% increase in dietary quality scores, whereas the control group improved by only 5%. Health outcomes also favored the personalized approach: participants in the experimental group experienced an average weight reduction of 3.0 kg (versus 1.0 kg in the control group), a 2.0% decrease in body fat percentage (versus 0.5%), and higher rates of normalized blood pressure (60% vs. 30%) and stable blood glucose levels (55% vs. 25%). Additionally, user satisfaction was significantly higher in the experimental group, with 80% of participants reporting positive experiences due to better alignment with individual dietary preferences and ease of adherence, compared to 50% in the control group, where feedback frequently noted the rigidity and low practicality of standardized plans. These results demonstrate the clinical and behavioral benefits of personalized, AI-assisted dietary interventions.

Table 1. Comparison of Experimental and Control Group Outcomes.

Metric	Experimental Group	Control Group
Increase in dietary quality score	15%	5%
Average weight loss	3 kg	1 kg
Reduction in body fat percentage	2%	0.5%
Proportion with normalized blood pressure	60%	30%
Proportion with stable blood glucose levels	55%	25%
User satisfaction rate	80%	50%

4.2. In-Depth Analysis

The findings support the effectiveness of the personalized nutrition system and highlight several core advantages that contributed to its enhanced performance. First, the application of Transformer-based deep learning algorithms enabled effective interpretation of heterogeneous health data, facilitating accurate alignment between dietary intake and individual metabolic profiles. Second, the incorporation of reinforcement learning techniques allowed for continuous optimization of dietary plans in response to evolving physiological states and behavioral patterns. Third, federated learning frameworks enabled model training across distributed datasets without compromising data privacy, thereby enhancing both model accuracy and population-level adaptability. Furthermore, the use of interpretable machine learning methods, including LIME and SHAP, improved transparency by providing clear rationale for the system's dietary outputs, which in turn supported user trust and adherence. The consistent outcome gap observed between the intervention and control groups underscores the practical utility of personalized nutrition strategies in the context of precision health and individualized wellness programs.

5. Conclusion

This study presents a personalized nutrition recommendation system built upon federated learning and the integration of multiple types of health data. By combining clinical, behavioral, and genetic information with established machine learning methods, the system provided tailored dietary suggestions while maintaining data confidentiality. Results from a six-month controlled intervention showed meaningful improvements in diet quality, health-related biomarkers, and user satisfaction compared to standard nutrition plans. The inclusion of interpretable machine learning techniques also improved the clarity of the system's decisions, making the outputs more understandable and acceptable to both users and healthcare providers.

Several limitations should be acknowledged. Participant dropout during the study led to a moderate reduction in the final sample size, which may affect the generalizability of the findings. Additionally, although federated learning successfully protected personal data, its implementation was affected by differences in data quality and communication delays across data sources. These factors may have influenced model performance and consistency during training.

Further research should aim to expand the participant population to include broader age ranges, regions, and health backgrounds to strengthen the applicability of the findings. Improvements to the federated learning process — particularly in handling uneven data and unstable network conditions — could enhance both accuracy and training efficiency. In addition, the exploration of data synthesis methods may help create more personalized dietary options for users with uncommon needs. Finally, combining the system with existing digital health tools, such as mobile health apps, home-use nutrition trackers, and wearable health monitors, could enable real-time support and long-term health monitoring. These developments may support the wider application of personalized nutrition approaches in both clinical care and preventive health programs.

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