AI-POWERED PERSONALIZED FITNESS AND DIET RECOMMENDATION SYSTEM USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

1Himanshu Tyagi, 2Honey Pal, 3Ashu Kaushik, 4Dishant Sharma
1,2,3,4Department of Computer Science Engineering (Data Science)
RD Engineering College, Ghaziabad, India

Abstract*—The increasing number of cases of lifestyle-related health problems such as obesity, diabetes, blood pressure, and heart disease indicates the urgency of a personalized health management system. Existing systems tend to be generic and fail to account for specific characteristics of an individual such as physiological metrics, physical activities, eating habits, and health objectives. This study proposes an AI-Powered Personalized Fitness and Diet Recommendation System using Machine Learning (ML) and Deep Learning (DL) techniques. The proposed system consists of a Convolutional Neural Network (CNN) to identify physical activities of users, collaborative filtering based recommendation algorithm for nutritional recommendations, and Reinforcement Learning (RL) for adaptive feedback. Physical attributes of the user such as body weight and age, along with health-related information including exercise and diet, are processed by a multi-modal pipeline in order to provide relevant recommendations at any required time.

***Index Terms* — Artificial Intelligence, Machine Learning, Deep Learning, Personalized Recommendation System, Fitness Tracking, Diet Planning, Collaborative Filtering, Convolutional Neural Network, Reinforcement Learning, Digital Health.**

I. Introduction

The global rate of non-communicable diseases (NCD) has reached alarming proportions. According to the World Health Organization (WHO), NCDs result in approximately 74% of all deaths worldwide, with poor dietary habits and physical inactivity being the two primary contributing factors. Despite widespread awareness, many individuals still lack access to affordable, personalized guidance from certified nutritionists and fitness experts. Traditional diet charts and workout plans are static, generic, and often ineffective because they do not adapt to a person's evolving health status, lifestyle changes, or individual preferences.

The rapid advancement of Artificial Intelligence (AI), particularly in the domains of machine learning and deep learning, presents a great opportunity to bridge this gap. AI-powered personalized health systems can analyze vast amounts of data—from wearable sensor outputs and food logs to genomic markers and stress indicators—to generate highly personalized, context-aware health recommendations. Existing commercial applications such as MyFitnessPal and Fitbit provide basic calorie tracking and step counting, but they rely primarily on rule-based logic and lack true adaptive intelligence. The absence of real-time personalization, cross-domain integration (fitness + diet), and long-term goal tracking remains a significant limitation in the current ecosystem.

This paper addresses these limitations by proposing an end-to-end AI-powered Fitness and Diet Recommendation System. The key contributions of this work are as follows:

- A multi-modal data integration pipeline that combines biometric, dietary, and activity data.
- A hybrid recommendation engine utilizing collaborative filtering and content-based filtering for meal planning.
- A CNN-LSTM model for activity classification and intensity prediction.
- A reinforcement learning module for adaptive, goal-oriented fitness plan adjustment.
- Comprehensive evaluation across multiple benchmark datasets with comparative analysis against existing state-of-the-art systems.

The remainder of this paper is organized as follows. Section II reviews related work. Section III defines the problem statement. Section IV presents the proposed framework. Section V details the methodology. Section VI discusses the results. Section VII outlines future scope, and Section VIII concludes the paper.

II. Related Work

Personalized health recommendation systems have been an active area of research over the past decade. Early systems relied heavily on knowledge-based approaches and clinical rule engines. With the emergence of big data and deep learning, however, the landscape has shifted considerably toward data-driven methods.

A. Dietary Recommendation Systems

Trang et al. proposed a food recommendation system using collaborative filtering combined with nutritional constraints optimization. Their system demonstrated improved meal adherence but was limited by the cold-start problem for new users. Similarly, Min et al. used deep learning for food recognition from images using CNN, achieving 89.2% classification accuracy, though this system lacked integration with personalized health metrics.

Rostami et al. introduced a hybrid filtering approach combining content-based and collaborative filtering techniques, addressing the data sparsity challenge. Their work, however, focused exclusively on dietary recommendations without any coupling with physical fitness planning.

B. Fitness and Physical Activity Recognition

Ordóñez and Roggen proposed a CNN-LSTM system architecture for recognizing activities using smartphones and wearable sensors, achieving state-of-the-art results on the OPPORTUNITY and PAMAP2 datasets. This work established a strong baseline for sensor-based human activity recognition (HAR).

Hammerla et al. conducted a systematic comparison of deep learning architectures for HAR and concluded that LSTM-based models consistently outperform traditional CNN and fully connected network approaches for time-series activity data.

C. AI-Powered Integrated Health Systems

Shu et al. proposed a reinforcement learning-based personalized health recommendation framework that modeled user behavior as a Markov Decision Process (MDP). Their results showed a 28% improvement in user engagement over static recommendation systems. However, the framework was tested only on a synthetic dataset and lacked real-world validation.

Zeevi et al. demonstrated that personalized dietary recommendations based on gut microbiome data and glycemic response were significantly more effective than generic dietary guidelines. This pioneering work highlighted the critical need for multi-modal data integration in health recommendation systems.

Despite these advances, no existing system fully integrates real-time activity recognition, adaptive dietary planning, and long-term goal tracking within a unified, scalable AI framework. The proposed system addresses this gap comprehensively.

III. Problem Statement

Let a user be represented by a feature vector U = {u1, u2, ..., un}, where each ui encodes a distinct health attribute such as age, gender, weight, height, Body Mass Index (BMI), resting heart rate, activity level, dietary restrictions, and health goals (e.g., weight loss, muscle gain, or endurance improvement).

The core problem is formalized as follows: given the user profile U, historical activity log A = {a1, a2, ..., aT} over T time steps, nutritional intake history D = {d1, d2, ..., dT}, and real-time biometric signals Bt at time t, generate a personalized recommendation pair $\hat{R}t = (\hat{F}t, \hat{M}t)$ where $\hat{F}t$ is the optimal fitness plan and $\hat{M}t$ is the optimal meal plan at time t, maximizing cumulative health goal attainment.

The primary challenges addressed in this work are:

Data Heterogeneity: Health data originates from diverse sources (wearables, dietary logs, medical records) with varying formats, sampling rates, and noise profiles.

Temporal Dynamics: User health status evolves over time; a static recommendation model becomes unsatisfactory rapidly.

Cold-Start Problem: Insufficient historical data for new users compromises recommendation quality.

Multi-Objective Optimization: Simultaneous optimization of caloric balance, macronutrient adequacy, and fitness progression requires conflict resolution among competing objectives.

User Adherence: Recommendations must be practically achievable and aligned with user preferences to maximize real-world compliance.

IV. Proposed Framework

A. System Architecture Overview

The proposed system, named FitAI, follows a five-layer architecture. The five layers are: (1) Data Acquisition Layer, (2) Preprocessing and Feature Engineering Layer, (3) AI/ML Model Layer, (4) Recommendation Engine Layer, and (5) User Interaction and Feedback Layer.

B. Data Acquisition Layer

In this layer, data is collected from the user through a form in which users provide details such as age, height, weight, and workout goals, which are then used to generate personalized workout and diet recommendations.

C. Preprocessing and Feature Engineering Layer

Raw data undergoes cleaning, normalization, and feature extraction. Missing values in time-series sensor data are imputed using Bidirectional LSTM (BiLSTM) autoencoders. Nutritional data is normalized to per-100g macronutrient profiles. Temporal features such as day-of-week patterns and circadian activity trends are extracted using a sliding window approach of window size w = 60 seconds for high-frequency sensor data.

D. AI/ML Model Layer

This layer comprises three core models:

Activity Recognition Module: A CNN-LSTM hybrid model processes tri-axial accelerometer and gyroscope data to classify 18 distinct activity types and estimate exercise intensity.

Nutritional Assessment Module: A Multi-Layer Perceptron (MLP) evaluates daily dietary intake against Recommended Dietary Allowances (RDA) and flags nutritional deficiencies.

Health State Predictor: A gradient boosting classifier (XGBoost) predicts short-term health trajectory based on recent behavioral patterns.

E. Recommendation Engine Layer

A hybrid recommendation engine combines:

Collaborative Filtering (CF): Matrix factorization using Singular Value Decomposition (SVD) to identify users with similar health profiles and recommend successful meal/workout plans.

Content-Based Filtering (CBF): TF-IDF weighted nutritional content vectors matched against user dietary constraints and preferences.

Reinforcement Learning (RL): A Deep Q-Network (DQN) agent models the long-term recommendation policy, maximizing cumulative health goal attainment reward.

F. User Interaction and Feedback Layer

A conversational AI interface (chatbot powered by a fine-tuned language model) allows users to query recommendations, log meals via natural language, and receive motivational feedback. Explicit (ratings) and implicit (adherence behavior) user feedback are continuously fed back to retrain the recommendation models online.

V. METHODOLOGY

A. Dataset

Three publicly available datasets were used:

PAMAP2 Physical Activity Monitoring Dataset: Contains IMU sensor data from 18 physical activities performed by 9 subjects wearing 3 inertial measurement units.

USDA FoodData Central: A comprehensive nutritional database of over 600,000 foods with detailed macro- and micronutrient profiles.

MyFoodRepo Dataset: 4,994 annotated food images used for food recognition training.

A synthetic user dataset was additionally generated using Monte Carlo simulation to model diverse health profiles (n = 10,000 users) for evaluating the recommendation engine.

B. CNN-LSTM Activity Recognition

Activity recognition was modeled as a multiclass time-series classification problem. Input data consists of windows of L = 128 samples from 6-channel IMU data (3-axis accelerometer + 3-axis gyroscope). The CNN component extracts local temporal features using 1D convolutions:

$$\eta(\lambda) = P\varepsilon\Lambda\Upsilon(\Omega(\lambda) * \xi(\lambda-1) + \beta(\lambda)) \qquad (2)$$

where * denotes 1D convolution, W(l) is the filter weight, and b(l) is the bias term. The LSTM layer captures long-range temporal dependencies:

$$\eta\tau = \Lambda\Sigma TM(\eta\tau-1,\ \xi\tau;\ \theta) \qquad (3)$$

The final classification layer uses softmax activation over C = 18 activity classes.

C. Hybrid Recommendation Engine

For the collaborative filtering component, the user-meal interaction matrix R ∈ R^(m×n) (where m = users, n = meals) is factorized as:

$$P\ H\ \Pi \bullet \Theta\perp T,\quad \Pi \square P\perp(\mu\cdot\kappa),\quad \Theta \square P\perp(\nu\cdot\kappa) \qquad (4)$$

where k is the latent factor dimension. Optimization is performed using Alternating Least Squares (ALS) with L2 regularization:

$$\Lambda = \copyright(\iota,\varphi)\square K\ (\rho\iota\varphi - \pi\iota\perp T\ \theta\varphi)\perp 2 + \lfloor(||\pi\iota||\perp 2 + ||\theta\varphi||\perp 2) \qquad (5)$$

D. Reinforcement Learning Module

The adaptive fitness planning problem is formulated as a Markov Decision Process (S, A, P, R, γ) where S represents the health state space (BMI trend, activity level, nutritional balance), A represents the action space (increase/decrease workout intensity, adjust macronutrient targets), and R is the reward function based on goal proximity and user adherence. A Deep Q-Network (DQN) with experience replay and target network stabilization is used to learn the optimal recommendation policy π*.

E. Evaluation Metrics

System performance was evaluated using: Precision@K, Recall@K, Normalized Discounted Cumulative Gain (NDCG), Root Mean Squared Error (RMSE) for nutritional predictions, F1-score for activity classification, and a user adherence rate computed over a 4-week simulated longitudinal study.

VI. RESULT AND DISCUSSION

A. Activity Recognition Performance

The CNN-LSTM model was trained for 100 epochs with a batch size of 64 and an Adam optimizer (lr = 0.001). Table I summarizes the classification performance on the PAMAP2 test set.

TABLE I

Activity Recognition Performance on PAMAP2 Dataset

Model	Accuracy	Precision	Recall	F1-Score
SVM (Baseline)	78.4%	77.9%	78.1%	78.0%
Random Forest	83.2%	82.7%	83.0%	82.8%
CNN Only	87.5%	87.1%	87.3%	87.2%
LSTM Only	88.9%	88.4%	88.7%	88.5%
CNN-LSTM (Proposed)	**93.7%**	**93.4%**	**93.5%**	**93.4%**

The CNN-LSTM model outperforms all baselines, achieving 93.7% accuracy. The improvement over pure CNN and LSTM models validates the complementary nature of local feature extraction and sequential pattern modeling for HAR.

B. Recommendation Engine Performance

Table II presents the comparative performance of the recommendation engine across different configurations.

TABLE II

Recommendation Engine Performance (K=10)

Method	Precision@10	Recall@10	NDCG@10
Content-Based Only	0.612	0.589	0.601
Collaborative Filter	0.698	0.673	0.684
Hybrid (CF + CBF)	0.741	0.718	0.729
Hybrid + RL (Proposed)	**0.813**	**0.791**	**0.802**

The addition of the RL module yields a 9.7% improvement in NDCG@10 over the hybrid CF+CBF baseline, demonstrating the value of long-term adaptive planning over static recommendation strategies.

C. User Adherence Simulation

Over a simulated 28-day period across 1,000 synthetic user profiles, the proposed system achieved a dietary adherence rate of 73.4% and a fitness plan completion rate of 68.9%, compared to 54.7% and 49.3% respectively for a rule-based control system. This represents a relative improvement of 34.2% in dietary adherence and 39.7% in fitness adherence.

D. Discussion

The results collectively validate the effectiveness of the multi-modal, adaptive AI approach. The CNN-LSTM model benefits from the spatial feature extraction capabilities of CNN layers combined with the temporal memory of LSTM, which is particularly well-suited to the quasi-periodic nature of physical activity signals. The RL-augmented recommendation engine demonstrates superior long-term performance by balancing immediate recommendation relevance with sustained goal progression.

One observed limitation is the degraded performance of collaborative filtering for users with fewer than 10 interaction records, confirming the cold-start challenge. The content-based fallback mitigates this partially, but incorporating demographic-based transfer learning is identified as a necessary improvement.

VII. Future Scope

Several promising directions exist for extending the proposed system:

Genomic and Microbiome Integration: Incorporating genomic markers and gut microbiome profiles can enable truly personalized dietary recommendations at the molecular level.

Mental Health and Stress Modeling: Integrating psychological stress indicators (cortisol levels, sleep quality, HRV patterns) into the health state representation can enable holistic wellness recommendations.

Federated Learning for Privacy Preservation: Deploying federated learning across user devices will allow model personalization without centralizing sensitive health data, addressing critical privacy and regulatory (HIPAA, GDPR) concerns.

Explainable AI (XAI): Incorporating explainability mechanisms such as SHAP values and LIME to make AI-generated recommendations interpretable and trustworthy to end-users and healthcare professionals.

Clinical Validation: A prospective randomized controlled trial (RCT) with real patients under clinical supervision is essential for validating the medical efficacy of the system and enabling regulatory approval as a digital health device.

Multi-Disease Management: Extending the system to support concurrent management of comorbidities such as Type 2 diabetes, hypertension, and dyslipidemia with clinician-in-the-loop oversight.

VIII. Conclusion

This paper presents FitAI, an AI-powered personalized fitness and diet recommendation system that integrates CNN-LSTM based activity recognition, hybrid collaborative and content-based filtering, and reinforcement learning for adaptive recommendations. The proposed model addresses the limitations of existing systems, including data heterogeneity, cold-start issues, temporal dynamics, and multi-objective optimization. Experimental results demonstrate significant performance improvements over baseline methods across all evaluated metrics.

As AI continues to evolve, its integration with precision medicine, wearable technology, and behavioral science holds the potential to democratize access to personalized health guidance—transforming reactive healthcare into proactive, preventative wellness management for populations worldwide.

References

[1] World Health Organization, "Noncommunicable diseases," WHO Fact Sheet, Sep. 2022. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases

[2] M. Chen, Y. Hao, K. Hwang, L. Wang, and L. Wang, "Disease prediction by machine learning over big data from healthcare communities," IEEE Access, vol. 5, pp. 8869–8879, 2017.

[3] H. T. Trang, N. T. Dung, and P. V. Nam, "A food recommendation system based on nutritional requirements and collaborative filtering," in Proc. Int. Conf. Advanced Comput. Appl., 2019, pp. 210–215.

[4] W. Min, B.-K. Bao, S. Mei, Y. Zhu, Y. Rui, and S. Jiang, "You are what you eat: Exploring rich recipe information for cross-regional food analysis," IEEE Trans. Multimedia, vol. 20, no. 4, pp. 950–964, 2018.

[5] M. Rostami, M. Oussalah, and V. Farrahi, "A novel time-aware food recommender system based on deep learning and graph clustering," IEEE Access, vol. 10, pp. 52508–52524, 2022.

[6] F. J. Ordóñez and D. Roggen, "Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition," Sensors, vol. 16, no. 1, p. 115, 2016.

[7] N. Y. Hammerla, S. Halloran, and T. Plötz, "Deep, convolutional, and recurrent models for human activity recognition using wearables," in Proc. 25th Int. Joint Conf. Artif. Intell., 2016, pp. 1533–1540.

[8] L. Shu, J. Xu, and H. Huang, "A reinforcement learning-based personalized health recommendation system," in Proc. IEEE Int. Conf. Healthc. Informatics, 2020, pp. 1–8.

[9] D. Zeevi et al., "Personalized nutrition by prediction of glycemic responses," Cell, vol. 163, no. 5, pp. 1079–1094, 2015.

[10] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.

[11] R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction, 2nd ed. Cambridge, MA, USA: MIT Press, 2018.