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AI Coach: Your Personalized Fitness and Diet Planner

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ABSTRACT

This paper presents the development of a web-based smart fitness tracker application that leverages machine learning to deliver personalized workout and dietary recommendations. Built using Streamlit, the system accepts user inputs like age, gender, weight, and goals to generate calorie-adjusted Indian meal plans and beginner-friendly exercise routines. It utilizes the Mifflin-St Jeor equation for BMR calculations and employs MongoDB for real-time data storage. Progressive overload is implemented using K-Means clustering and Standard Scaler to suggest weekly weight increments based on workout logs. Users can visualize trends and track performance with interactive dashboards. Unlike traditional fitness apps, the proposed system minimizes manual effort and adapts dynamically to user progress. The integration of data analytics ensures more accurate and goal-specific planning. This project highlights the shift from static tracking to intelligent, user-centered wellness solutions. Overall, it provides a scalable and accessible platform for proactive personal health management.

Keywords: Smart Fitness Tracker, Machine Learning, Personalized Workout, Calorie Estimation, Progressive Overload, K-Means Clustering, MongoDB, Web Application, Adaptive Feedback, Health Monitoring

1. Introduction

The increasing use of web-based fitness applications has paved the way for intelligent health monitoring solutions beyond traditional step counting and static meal tracking. This paper presents a smart fitness tracker developed using Streamlit, integrating machine learning for personalized diet and workout recommendations. By collecting user inputs such as age, gender, weight, and fitness goals, the system generates adaptive plans using real-time data analytics. MongoDB serves as a scalable backend for storing user logs, while K-Means clustering supports progressive overload analysis. The solution emphasizes data-driven insights, enabling users to visualize trends and receive weekly updates tailored to their performance. This project highlights the shift toward intelligent, user-centric fitness systems that promote sustainable health outcomes. The proposed model aims to enhance user engagement and decision-making through automation, personalization, and interactive feedback.

2. Literature Review

Recent studies demonstrate the growing role of machine learning in enhancing digital fitness applications through personalized workout and diet recommendations. Gupta et al. (2023) emphasized adaptive learning models for progressive overload, aligning with this project's use of K-Means clustering to analyze workout data and recommend weekly intensity adjustments. Sharma et al. (2022) focused on anomaly detection using wearable sensors, a concept that lays the foundation for potential expansion into real-time health monitoring in future iterations. Patel et al. (2021) introduced ML-based activity recognition through sensor fusion, which supports the automation of user input in fitness trackers. Lee and Kim (2020) proposed an AI-based nutritional system that adapts to user energy expenditure—reflected in this project's use of Mifflin-St Jeor-based calorie estimation and dynamic Indian meal planning. These approaches converge toward a common goal: empowering users through data-driven decisions and sustainable behavior change. The integration of MongoDB for scalable storage and Streamlit for a lightweight frontend also aligns with literature trends advocating real-time, accessible, and cloud-enabled health solutions.

3. Methodology

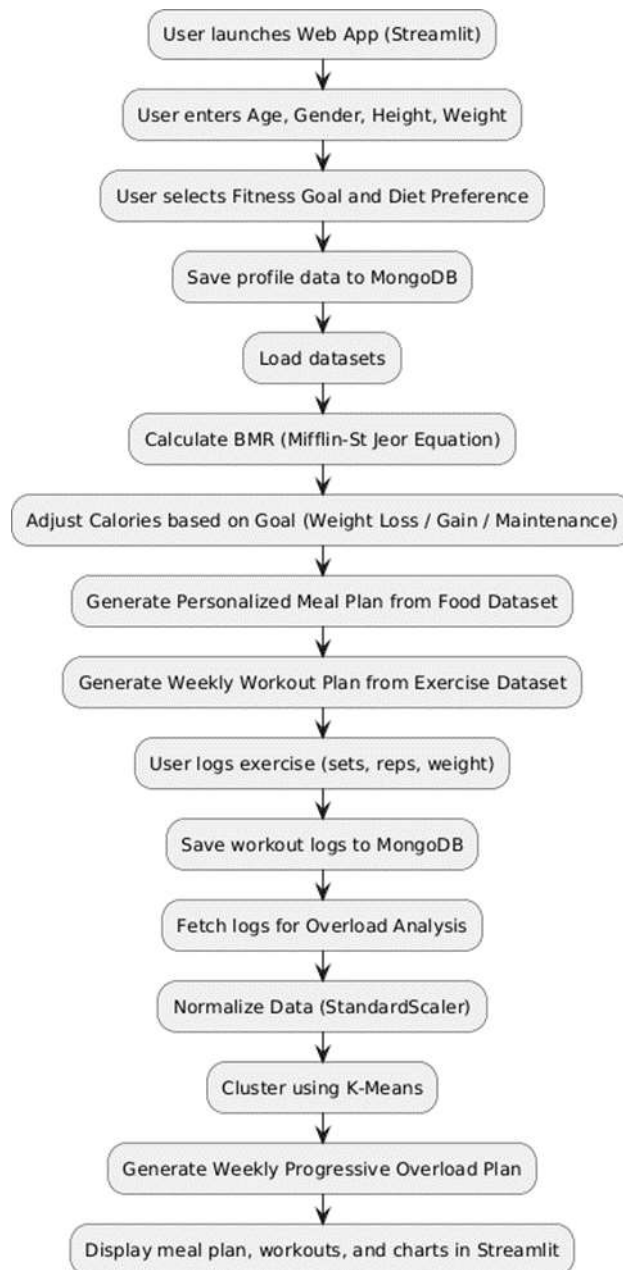


Fig - 1: Methodology for Fitness Tracker

The proposed system, *Fitness Tracker*, is a web-based application that uses machine learning and user profiling to deliver personalized fitness and diet recommendations. The methodology is organized into five core phases: **User Input Collection**, **Calorie & Workout Planning**, **Progress Logging**, **Machine Learning-Based Overload Analysis**, and **Interactive Visualization**, as illustrated in Figure 1.

In the **User Input Collection** phase, the user launches the application through a Streamlit interface and enters personal information such as age, gender, height, weight, fitness goals, and dietary preferences. This data is securely stored in a MongoDB database.

Next, during the **Calorie & Workout Planning** phase, the system loads predefined datasets of Indian food items and beginner-level exercises. Using the Mifflin-St Jeor equation, the application calculates the user's Basal Metabolic Rate (BMR), which is adjusted according to the user's fitness goals (e.g., weight loss, maintenance, or muscle gain). The system then generates a personalized meal plan and a 7-day workout schedule tailored to the user's preferences.

In the **Progress Logging** phase, users log their daily workouts, including the number of sets, reps, and weights used. These entries are saved in MongoDB for further analysis and visualization.

The **Machine Learning-Based Overload Analysis** phase begins by retrieving the logged workout data, applying normalization using Standard Scaler, and clustering intensity levels with the K-Means algorithm. This analysis helps the system recommend progressive overload plans by gradually increasing weight targets over subsequent weeks.

Finally, the **Interactive Visualization** phase displays personalized meal plans, workout history, and overload recommendations using Streamlit tables and charts. This real-time feedback loop ensures that users can monitor progress, receive adaptive updates, and stay engaged in their fitness journey.

This structured methodology transforms the Fitness Tracker into a dynamic and intelligent wellness assistant that adapts continuously to user behavior and goals.

3.1.1 User Input and Profile Handling

- The user accesses the **Streamlit-based web application**.
- Inputs personal details: **Age, Gender, Height, Weight, Fitness Goal** (e.g., Weight Loss, Muscle Gain), and **Diet Preference** (Veg/Non-Veg).
- These inputs are securely **stored in MongoDB** to generate personalized plans and support progress tracking.

3.1.2 Data Loading and Preprocessing

Two CSV datasets are loaded:

- **Indian Food Dataset:** Contains meals with categories (Breakfast, Lunch, etc.) and nutritional values.
- **Workout Dataset:** Contains beginner-friendly exercises with default sets, reps, and weights. Data is cleaned and standardized.

Caloric needs are calculated using the **Mifflin-St Jeor Equation**, and adjusted based on fitness goal.

3.1.3 Meal & Workout Plan Generation

- The application filters food items based on **diet type** and allocates meals across 4 categories per day.
- A **7-day workout plan** is generated using randomized exercises from the dataset.
- The generated plans are displayed interactively using **Streamlit tables and UI blocks**.

3.1.4 Workout Logging and Progress Tracking

- The user logs daily workouts (exercise name, sets, reps, weight used).
- These logs are **stored in MongoDB** with timestamps.
- Users can retrieve and view their history via dynamic tables in the frontend.

3.1.5 AI Tutoring Integration

- Logged workout data is retrieved and **normalized using StandardScaler**.
- **K-Means clustering** is applied to identify performance intensity levels.
- Based on the cluster, the system **recommends weekly progressive overload** (e.g., +5% weight increase per week).
- Results are visualized in charts or tables using Streamlit.

3.1.6 Technology Stack

Component	Technology
Frontend	Streamlit
Backend	Python (Pandas, Sklearn)
Database	MongoDB (via PyMongo)
ML Algorithms	StandardScaler, K-Means

3.1.7 Deployment

- The solution is **web-based and lightweight**.
- Easily deployable on local machines or cloud platforms.
- Supports interactive usage without requiring complex infrastructure.

3.2 System Architecture



Here's a structured breakdown of your **Fitness Tracker Using Machine Learning** system, described in the same modular, narrative style as the Code Visualizer example:

The Fitness Tracker system follows a modular architecture designed for personalization, real-time progress tracking, and intelligent fitness recommendations. The application is divided into distinct modules that interact cohesively to deliver a seamless and adaptive user experience. Here's how the system flows, starting from user interaction and culminating in intelligent analytics:

1. User Interface (Streamlit Frontend):

The primary access point where users input personal details, fitness goals, and workout logs. The interface includes interactive tabs for calorie calculation, meal planning, progress tracking, and overload analysis.

2. Profile & Goal Form Module:

This component captures demographic and lifestyle data like age, gender, height, weight, fitness goals, and diet preferences. It uses the Mifflin- St Jeor equation to estimate daily calorie needs.

3. Meal Planner Module:

Based on the user's diet preference and caloric requirement, this module filters an Indian meals dataset and generates randomized yet balanced daily meal suggestions for Breakfast, Lunch, Snack, and Dinner.

4. Workout Generator Module:

A beginner-friendly workout planner draws from a curated dataset to assign daily exercise routines. These routines include suggested sets, reps, and starter weight ranges.

5. Progress Tracker Module (MongoDB Logging):

Allows users to record workout details like exercise name, sets, reps, weight used, and day. These records are securely stored in MongoDB for future performance analysis.

6. Progressive Overload Analyzer:

This machine learning module retrieves past workout logs and applies data normalization (StandardScaler) followed by K-Means clustering. It generates a 5-week progressive weight increase plan tailored to the user's trends and training intensity.

7. Final Output Renderer:

This layer compiles the results of meal plans, workout schedules, tracked logs, and overload projections. Outputs are visually rendered using Streamlit's data frames, graphs, and styled containers, offering an intuitive snapshot of the user's fitness journey.

4. Work Flow

The AI-Based Smart Fitness Tracker web application follows a structured, interactive workflow designed to guide users through personalized fitness planning, real-time progress logging, and adaptive overload analysis. The complete workflow is detailed below:

Step 1: User Input Collection

The user accesses the web-based Streamlit interface and enters personal details including name, age, gender, height, weight, dietary preference, and fitness goal. These inputs are used to tailor calorie needs, meal recommendations, and workout routines. The form ensures all data is cleanly formatted and ready for processing.

Step 2: Calorie & Meal Planning

Once submitted, the backend calculates the user's Basal Metabolic Rate (BMR) using the Mifflin-St Jeor Equation. Based on the fitness goal (weight loss, muscle gain, or maintenance), it computes the daily calorie target. The system then loads the food dataset (CSV) and filters meal items (breakfast, lunch, snacks, dinner) according to diet preference (Veg/Non-Veg), generating a balanced daily and weekly meal plan.

Step 3: Workout Plan Generation

In parallel, the application loads a structured workout dataset to randomly generate a beginner-friendly, 7-day workout plan. Each day features exercises with predefined sets, reps, and weights. This plan is displayed clearly for easy user reference.

Step 4: Real-Time Progress Logging

Users can log daily workout details (exercise name, sets, reps, and weight used) into the system through a dedicated input form. These entries are stored in a MongoDB collection, indexed by user name and date, enabling persistent, cloud-based storage and historical tracking.

Step 5: Progressive Overload Analysis

As users accumulate workout logs, the backend retrieves these records and applies Standard Scaler to normalize the weights. It then uses K-Means Clustering to categorize exercises by intensity level. Based on the user's current cluster, the system generates a week-by-week progressive overload plan (+5% weight increment weekly), which is then displayed in tabular and graphical formats.

Step 6: Visualization & Feedback

The application visualizes the user's workout progress, average weights lifted, and overload recommendations via Streamlit charts and tables. This feedback loop helps users track improvements and adjust efforts over time.

Step 7: Learning & Adaptation

By combining static data (user input), dynamic data (exercise logs), and machine learning insights (cluster-based overload plans), the tracker ensures adaptive planning.

The system refines recommendations as more logs are added, closing the feedback loop between planning, execution, and progress—offering a personalized, evolving fitness experience.

5. Output Screens

The screenshot displays the 'Personalized Fitness Tracker' web application. The main heading is 'Calorie Calculator & Weekly Plan'. Below it, there is a form with the following fields:

- Enter your name: [Text input field]
- Gender: [Dropdown menu with 'Select' option]
- Age: [Text input field with value '20']
- Height (cm): [Text input field with value '170']
- Weight (kg): [Text input field with value '60']
- Diet: [Dropdown menu with 'Select' option]
- Goal: [Dropdown menu with 'Select' option]

A blue 'Generate Plan' button is located at the bottom left of the form. The background of the page features a collage of various fruits and vegetables.

Fig – 1: User Interface

This screenshot shows the same 'Personalized Fitness Tracker' web application, but with input values entered into the form fields:

- Enter your name: [Name input field]
- Gender: [Dropdown menu with 'Male' selected]
- Age: [Text input field with value '20']
- Height (cm): [Text input field with value '180']
- Weight (kg): [Text input field with value '55']
- Diet: [Dropdown menu with 'Non-Vegetarian' selected]
- Goal: [Dropdown menu with 'Muscle Gain' selected]

The blue 'Generate Plan' button remains at the bottom left. The background collage of fruits and vegetables is still visible.

Fig – 2: Enter input values



Fig-3(i): Result for given inputs

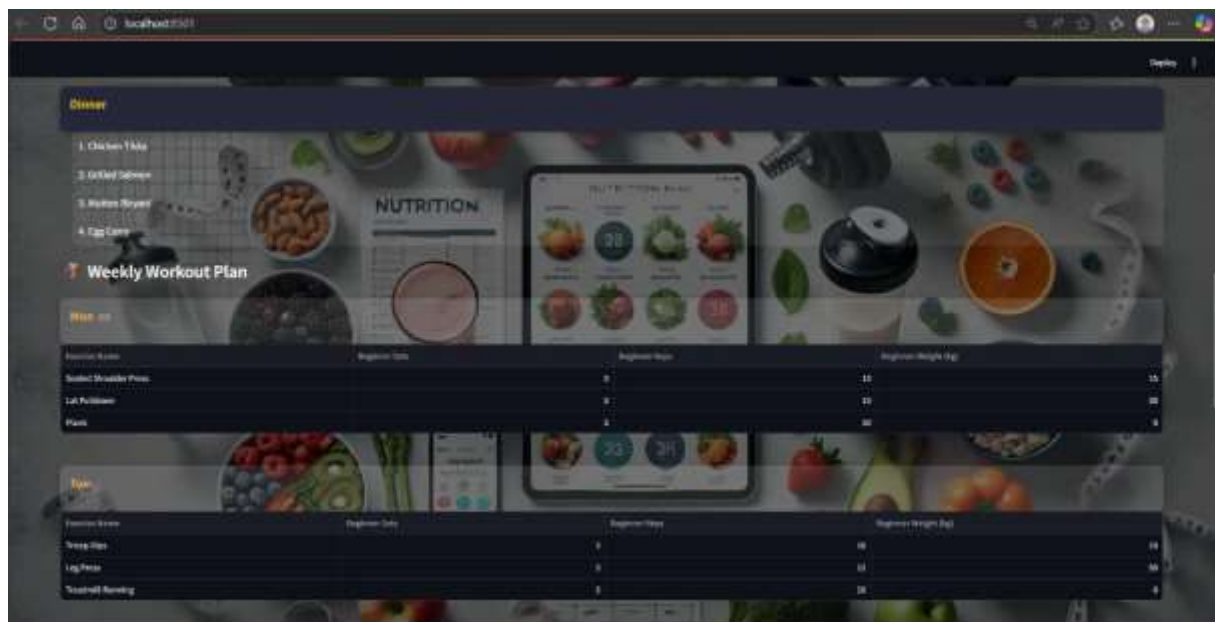


Fig – 3(ii): Result for given inputs

localhost:8501

Deploy

Wed

Exercise Name	Beginner Sets	Beginner Reps	Beginner Weight (kg)
Hamstring Curls	3	12	20
Bicep Curls	3	12	10
Chest Fly	3	10	12

Thu

Exercise Name	Beginner Sets	Beginner Reps	Beginner Weight (kg)
Deadlift	3	10	40
Barbell Rows	3	12	25
Squat	3	12	30

Fri

Exercise Name	Beginner Sets	Beginner Reps	Beginner Weight (kg)
Tricep Dips	3	10	10
Squat	3	12	30
Seated Shoulder Press	3	10	15

Fig – 3(iii) Result for given inputs

localhost:8501

Deploy

Personalized Fitness Tracker

Calorie & Meal Plan | Progress Tracking | Progress Overview

Progress Tracking

Enter your name for this & view progress

NAME

Exercise

Bench Press

Sets

5

Reps

6

Weight Used (kg)

33

Date

Monday

Save Progress

Progress saved!

View Progress

Fig – 4: Save progress



Fig – 5: View progress



Fig – 6: View Progressive Overloading

6. Conclusion and Future Scope

The development of the AI-Based Smart Fitness Tracker marks a transformative step in personalized digital health management. By leveraging machine learning techniques such as K-Means clustering and Standard Scaler, this web application effectively personalizes diet plans and progressive workout recommendations based on individual user inputs. With its Stream lit interface and real-time MongoDB integration, the system offers seamless user experience in tracking fitness progress and visualizing performance trends.

The project addresses key limitations of traditional fitness apps by automating data-driven planning and delivering dynamic feedback. It bridges the gap between user input and adaptive health recommendations, thereby promoting consistent fitness adherence, optimized strength training, and informed nutritional planning. The inclusion of personalized meal filtering based on Indian cuisine and fitness goals further enhances user engagement, making the tracker culturally relevant and accessible.

Future Scope:

Potential improvements and extensions of the include:

- **Wearable Device Integration:** Incorporate real-time sensor data for automatic logging and health anomaly detection.

- **Advanced Health Monitoring:** Enable alerts for irregularities in workout or vital data, enhancing preventive health care.
- **Mobile Application:** Develop Android and iOS apps to broaden accessibility and support cross-platform use
- **AI-Based Chat Assistant:** Introduce an AI health assistant to guide users with fitness and nutrition advice dynamically.
- **Gamification Features:** Add progress badges, streak counters, and leaderboards to motivate long-term fitness commitment.
- **Multilingual Support:** Support multiple Indian languages for broader user inclusivity.

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