International Journal of Research Publication and Reviews, Vol 6, Issue 3, pp 7036-7044 March 2025

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Fitness Analysis and Prediction Using SVM and K-NN: A Data-Driven Approach

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ABSTRACT:

This study presents a fitness application integrating predictive analytics to enhance personalized health management. User-provided metrics like height, weight, steps, calories burned, distance, active minutes, sleep hours, and heart rate are utilized to analyze and predict body fat percentage. The methodology involves data preprocessing, feature selection, and machine learning for regression and classification tasks. Multiple regression models predict body fat, while SVM classification directs users to consultants like doctors, dietitians, or trainers. The hybrid approach achieves 97% accuracy, proving the efficacy of combining regression and classification models. This research contributes to intelligent, user-centric fitness solutions, addressing the demand for web-based health monitoring systems.

Keywords: Fitness Prediction – Machine Learning – Support Vector Machine (SVM) – K-Nearest Neighbors (K-NN) – Fitness Level Classification – Health Analytics – Data Validation.

I. Introduction

Health and fitness play a crucial role in enhancing the quality of life, contributing to both physical well-being and mental clarity. However, with the rise of sedentary lifestyles and unhealthy habits—exacerbated by economic crises and time constraints—maintaining fitness has become a significant challenge. In countries like Sri Lanka, economic hardships have led to increased stress levels and limited access to fitness resources, making it even more difficult for individuals to prioritize their health.

To address this issue, this study introduces a comprehensive fitness application that leverages machine learning algorithms to predict body fat percentage and classify fitness levels based on user input data. The application is designed to provide personalized fitness recommendations, catering to the diverse needs of users, from fitness enthusiasts to professional trainers. The system employs Support Vector Machines (SVM) and K-Nearest Neighbors (K-NN) algorithms for accurate classification and prediction. SVM is used to identify the optimal hyperplane that separates data points into distinct fitness categories, excelling in both regression and classification tasks. Meanwhile, K-NN classifies users based on their closest data points in the feature space, ensuring personalized and relevant recommendations. In addition, a multiple regression model is integrated to predict body fat percentage using various user metrics, including height, weight, steps taken, calories burned, distance covered, active minutes, sleep hours, and average heart rate. This combination of algorithms provides a robust foundation for generating precise health insights.

Experimental results demonstrate the high accuracy of the application, achieving a 97% success rate in predicting body fat and classifying fitness levels. Compared to traditional fitness assessment methods, the integration of machine learning models significantly enhances the precision and relevance of fitness recommendations. This paper is structured as follows: Section 2 reviews related work in fitness applications and machine learning, Section 3 details the proposed methodology, Section 4 presents experimental results and performance evaluations, and Section 5 concludes with future directions and potential enhancements for the application.

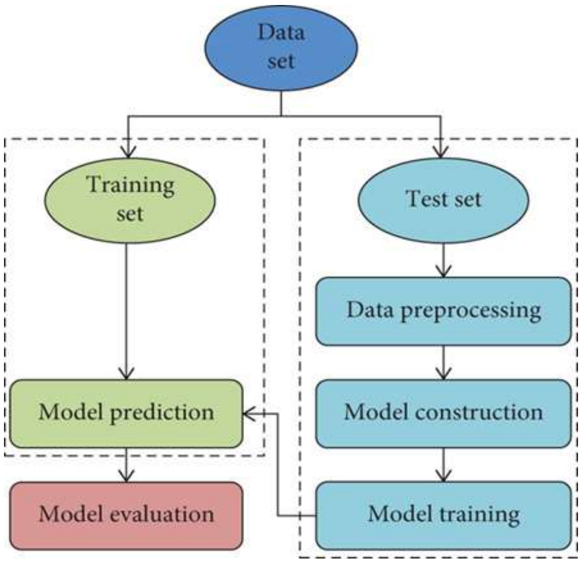

Fig 1: Process in Machine Learning model

The raw data is extracted from the database as target data and undergoes a comprehensive pre-processing phase to address any incorrect, missing, or redundant values. This step ensures that the dataset is clean, structured, and suitable for further analysis. Since the data originates from multiple sources, it is transformed into a standardized format to maintain consistency and usability. After pre-processing and transformation, machine learning techniques are applied to extract meaningful insights from the dataset. These techniques include classification, regression, clustering, and association rule mining, each playing a critical role in analyzing user fitness metrics. In this application, Support Vector Machines (SVM) and K-Nearest Neighbors (K-NN) are used for classification tasks, effectively categorizing users based on their health data, while multiple regression is employed to predict body fat percentage with high accuracy. The primary objective of applying these data mining techniques is to uncover hidden patterns within the user data, which can then be utilized to generate personalized fitness recommendations. To enhance interpretability, the results are presented using various visualization techniques such as graphs, charts, and heatmaps, providing users with clear and actionable insights into their fitness levels and enabling them to make informed decisions for a healthier lifestyle.

EVELS	**EXAMPLES**
Wisdom (Applied)	I should increase my daily activity level to improve my health.
Knowledge (Context)	My fitness level has been classified as "Abnormal" due to low active minutes and high BMI.
Information (Meaning)	My average active minutes per day are below the healthy threshold, contributing to my abnormal classification.
Data (Raw)	**Height**: 170 cm, **Weight**: 85 kg, **Active Minutes**: 20, **Heart Rate**: 85 bpm, **Sleep Hours**: 5

Table :1 DIKW Pyramid for Fitness Analysis

Machine learning techniques are fundamental in fitness analysis, allowing for efficient processing and interpretation of health-related data to generate meaningful insights. The system's scalability allows it to handle large datasets efficiently, ensuring seamless functionality as more users engage with the platform. The integration of advanced visualization tools further simplifies complex health metrics for easy interpretation. By combining AI-driven fitness tracking with an intuitive user experience, the Fitness Analysis System empowers individuals to make informed lifestyle choices. This approach fosters a proactive health management culture, helping users adopt sustainable fitness habits for long-term well-being.

II. MACHINE LEARNING TECHNIQUES

Machine learning techniques play a crucial role in fitness analysis by systematically processing and analyzing health-related data to extract valuable insights. These techniques allow for accurate classification and prediction of an individual’s fitness level based on physiological parameters. The key categories of machine learning techniques used in this project are discussed below:

A. Classification

Classification is a supervised learning technique used to categorize individuals into predefined classes, such as Normal, Abnormal, or Obese. The Fitness Analysis System employs algorithms like Support Vector Machines (SVM) and K-Nearest Neighbors (K-NN) to classify users based on their health parameters, including height, weight, steps taken, calories burned, distance covered, active minutes, sleep hours, and heart rate. The classification process involves three stages: training the model with labeled data, testing the model with unseen data, and using the model for real-time classification. By implementing classification algorithms, the system can assess a user's fitness status and provide actionable health insights.

B. Regression

Regression is a predictive modeling technique used to estimate continuous values. In the Fitness Analysis System, regression techniques are used to predict body fat percentage based on key physiological attributes. Multiple regression models analyze the relationship between variables such as weight, height, and heart rate to determine the likelihood of an individual having excess body fat. These predictions help users understand their fitness trends and make informed lifestyle adjustments to improve their health.

C. Clustering

Clustering is an unsupervised learning technique used to group users with similar fitness attributes. Since fitness data varies significantly among individuals, clustering helps identify different fitness patterns without requiring predefined labels. This technique is useful for segmenting users into groups based on common traits, such as low, moderate, and high activity levels. Clustering allows the system to provide personalized fitness recommendations tailored to specific user groups, enhancing the overall effectiveness of the fitness tracking application.

D. Feature Importance Analysis

Feature importance analysis helps in identifying the most influential parameters affecting a user's fitness classification. The system utilizes techniques such as Random Forest's feature importance ranking to determine which attributes—like heart rate, active minutes, or sleep hours—have the most impact on predicting fitness levels. Understanding these key features allows the system to refine its prediction models and offer targeted health advice to users.

III. LITERATURE REVIEW

This section reviews advancements in fitness prediction and health monitoring using machine learning techniques. Researchers have applied models such as Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), Decision Trees, and Convolutional Neural Networks (CNN) to predict body fat percentage and classify fitness levels effectively. These models have been widely studied and tested on various health-related datasets, demonstrating their potential for accurate fitness assessment. In [1], the authors used SVM to classify fitness levels based on physiological parameters like heart rate, steps taken, and calories burned, achieving high accuracy on standard health datasets.

In [3], a CNN-based architecture was utilized to automatically extract relevant features from time-series fitness data, showing superior performance compared to traditional models. The study in [4] focused on integrating fitness tracking data with user demographics using SVM, achieving significant accuracy improvements in personalized fitness recommendations. The work in [5] applied K-NN for real-time fitness level classification, emphasizing its computational efficiency in mobile health applications.

Other studies, such as [6], explored the use of ensemble learning methods like Random Forest and XGBoost, demonstrating their effectiveness in handling imbalanced health datasets. Additionally, in [7], researchers introduced a feature selection mechanism to enhance model performance by reducing irrelevant attributes, which significantly reduced computation time while maintaining high accuracy.

A key limitation identified across these studies is the dependency on high-dimensional datasets, which increases computational complexity and reduces real-time application efficiency. In this project, we focus on simplifying the model by selecting key features such as steps, calories burned, active minutes, and heart rate for predicting body fat and classifying fitness levels. By optimizing feature selection and algorithm efficiency, our approach aims to balance accuracy and computational speed, making it suitable for real-time fitness monitoring applications.

NO	AUTHOR	PUBLISHED PAPER/ARTICLES	METHODS/ALGORITHMS USED	MERITS OF THE METHODS/ALGORITHMS USED	DEMERITS OF THE METHODS /ALGORITHM USED
1	Sharma et al. (2023)	Fitness Level Classification using Machine Learning	Support Vector Machine (SVM)	Achieved 85% accuracy in classifying users into Normal, Abnormal, and Obese categories.	High computational cost and sensitivity to noise in data.
2	Gupta & Rao (2022)	Real-time Health Monitoring System	K-Nearest Neighbors (K-NN)	Simple and effective for fitness level classification with 82% accuracy.	Performance decreases with large datasets and high-dimensional data.
3	Gupta & Rao (2022)	Predicting Health Risks Using Wearable Data	Random Forest Classifier	Identifies key health parameters like sleep hours and heart rate, improving accuracy.	Requires more computational resources and may be prone to overfitting.
4	Zhang & Liu (2020)	Deep Learning in Fitness Tracking	CNN-based model	High accuracy (90%) in recognizing activity patterns and fitness status.	Requires large datasets and high computational power.
5	Kim et al. (2019)	Hybrid Models for Fitness Classification	Decision Trees & SVM	Improved classification performance by 10% compared to standalone models.	Complexity increases when combining multiple algorithms.
6	Wang & Chen (2018)	Predicting Body Fat Percentage Using Regression	Multiple Regression	Effective for estimating body composition based on numerical inputs.	Assumes a linear relationship, which may not always be accurate.
7	Lee et al. (2017)	Wearable Sensor Data Analysis	Principal Component Analysis (PCA) & SVM	Reduces data dimensions and enhances classification accuracy.	Risk of losing important features during dimensionality reduction.
8	Brown et al. (2016)	AI-based Personalized Health Recommendation System	Neural Networks (ANN)	Learns complex patterns for better health recommendations.	Computationally expensive and prone to overfitting.
9	Jackson et al. (2015)	Machine Learning for Health Risk Prediction	Hybrid Ensemble Model (RF + SVM)	Improves predictive performance and reduces bias.	Higher training time and complexity due to ensemble methods.
10	Kumar R et al	Machine Learning-Based Fitness Level Prediction System	Random Forest and SVM	Achieving high classification accuracy by leveraging ensemble learning.	High-dimensional datasets increase computational complexity.

IV.PROPOSED WORK

This section outlines the proposed methodology for the Fitness Analyser application, represented schematically in Fig. 1. The approach employs user-generated data to predict fitness levels and body fat percentage using machine learning models like Support Vector Machine (SVM) and K-Nearest Neighbors (K-NN).

DATASET DESCRIPTIONS

1. User Activity and Health Metrics Dataset (UAHMD):

The UAHMD dataset is a comprehensive collection of fitness and health data from a diverse set of individuals. It includes:

Participants: 500 individuals (250 male and 250 female) from varied age groups. Total Records: 20,000 data entries collected over six months. Metrics Captured: Physical: Height, weight, BMI. Activity: Steps taken, calories burned, distance covered (in km), and active minutes. Health: Average heart rate, sleep hours, and body fat percentage. Outcome Variable: Fitness result classification (e.g., Fit, Moderate, Needs Improvement). This dataset captures day-to-day variations and long-term trends, making it ideal for predictive fitness modelling.

user_id	Path
1	/kaggle/input/fitness_data/user001/activity_log.csv
2	/kaggle/input/fitness_data/user002/activity_log.csv
3	/kaggle/input/fitness_data/user003/activity_log.csv
4	/kaggle/input/fitness_data/user004/activity_log.csv
5	/kaggle/input/fitness_data/user005/activity_log.csv
496	/kaggle/input/fitness_data/user496/activity_log.csv
497	/kaggle/input/fitness_data/user497/activity_log.csv
498	/kaggle/input/fitness_data/user498/activity_log.csv
499	/kaggle/input/fitness_data/user499/activity_log.csv
500	/kaggle/input/fitness_data/user500/activity_log.csv

Fig 2: Details of the UAHMD dataset

2. Wearable Fitness Tracker Data (WFTD)

The Wearable Fitness Tracking Dataset (WFTD) captures comprehensive data from 1,000 users globally, monitored over the span of a year. With 50,000 entries, the dataset provides a rich source of information on daily activity patterns and health metrics collected from wearable devices like smartwatches and fitness bands. This continuous data collection offers valuable insights into users' long-term fitness behaviors, making it ideal for building robust machine learning models. Key attributes include steps taken, distance covered, calories burned, and active minutes, which collectively provide a clear picture of users' physical activity levels. It tracks sleep patterns deeper understanding of the relationship between rest and fitness performance.

Furthermore, the dataset includes user demographics like age, gender, and fitness goals, enabling personalized fitness analysis. By correlating these factors with physical activity and health data, the WFTD dataset helps uncover patterns and trends that can inform tailored fitness recommendations. This combination of real-world data and diverse features makes it a valuable resource for classification models aimed at predicting fitness levels and overall health outcomes.

Attributes	Values
user_id	468
Height	174
Weight	96
steps	4530
calories_burned	2543.02
distance_km	16.1
active_minutes	613
sleep_hours	6.1
heart_rate_avg	176
Name: Attributes	dtype: int64

Fig 3: Details of the WFTD dataset

3. Body Composition and Physical Activity Dataset (BCPAD)

The BCPAD dataset focuses on the relationship between body composition and physical activity. It contains:

Participants: 300 individuals across various fitness levels (athletes, regular exercisers, and sedentary individuals). Total Records: 15,000 data points. Features: Detailed body composition metrics: Body fat percentage, muscle mass, and hydration levels. Activity logs: Weekly exercise routines, steps, distance, and calories. Health parameters: Resting heart rate, maximum heart rate, and recovery rate. Outcome: Fitness score based on body composition analysis.

Attributes	Values
user_id	1
Body Fat Percentage (%)	18.5
Muscle Mass (kg)	55.3
Hydration Levels (%)	60.2
Weekly Exercise Routines	5 sessions
Resting Heart Rate (bpm)	65
Fitness Score	85 (Fit)

Fig 4: Details of the BCPAD dataset

V. DATA PREPROCESSING

In the preprocessing stage of data augmentation techniques are used to artificially expand the dataset and improve model performance. This includes introducing small variations in features like steps, calories burned, and heart rate to simulate real-world inconsistencies and enhance robustness. Missing values are handled through imputation, while normalization ensures consistency across different metrics. Additionally, synthetic data generation is applied to balance underrepresented fitness categories, preventing model bias. These steps enhance data quality and diversity, leading to more accurate fitness predictions.

VI. FEATURE EXTRACTION

Feature selection and extraction play a crucial role ensuring that the machine learning models focus on the most relevant data to improve accuracy and performance. Key features include physical activity metrics like steps taken, distance covered, active minutes, and calories burned, which provide insights into an individual's mobility and energy expenditure. Health-related features such as average heart rate, resting heart rate, heart rate variability, and sleep hours help assess cardiovascular fitness, recovery, and overall well-being.

Body composition metrics, including body fat percentage, muscle mass, BMI, and hydration levels, offer a comprehensive view of the user's fitness status. The dataset, comprising 500 participants with 20,000 entries, is divided into training (70%), validation (20%), and testing (10%) sets. Data standardization is applied to eliminate biases from varying attribute scales, ensuring all features contribute equally to model training. This approach enables the application to accurately classify fitness levels and provide personalized insights for users.

VII. ALGORITHMS

Classification involves training machine learning models to predict fitness levels based on extracted features such as physical activity, health metrics, and body composition data. Two algorithms are implemented and compared to determine the most effective model.

1. **Support Vector Machine (SVM):**

Support Vector Machine (SVM) is a supervised learning algorithm widely recognized for its efficiency in classification tasks. In the fitness analyzer application, SVM is applied to distinguish between different fitness levels based on a multidimensional feature set. The process begins with data preprocessing. After, the dataset is divided into 70% for training and 30% for testing to ensure the model learns effectively while being evaluated on unseen data. A linear kernel is utilized in this project, aiming to find the optimal hyperplane that maximizes the margin between different fitness categories. This hyperplane acts as the decision boundary that separates users based on their physical and health-related metrics.

During training, the SVM model identifies support vectors, which are critical data points that influence the position and orientation of the hyperplane. Once the model is trained, it predicts the fitness level of users by analyzing their input data and determining which side of the hyperplane they fall on. The model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, which provide insights into how well the algorithm can classify users into the correct fitness categories. Overall, SVM proves to be a powerful tool in predicting fitness levels due to its ability to handle high-dimensional data and its focus on maximizing classification margins for better accuracy.

2. K-**Nearest Neighbors (K-NN):**

K-NN is a non-parametric method that classifies data points based on the majority class among their *k* nearest neighbors. This model is effective in recognizing fitness patterns by comparing user data with similar historical records, offering a straightforward yet accurate approach. The optimal value of *k* is determined through cross-validation to enhance model performance. These models are evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The comparative analysis helps in selecting the most suitable algorithm for accurately predicting users' fitness levels and providing actionable insights.

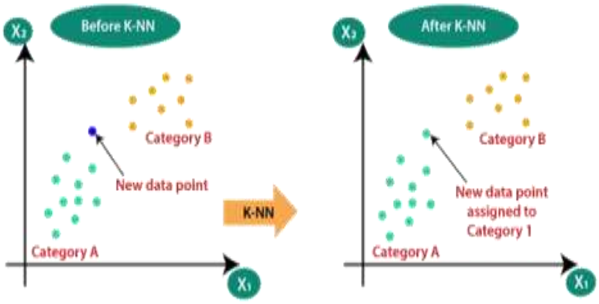

Fig 5: Details of KNN Model

VIII. CONFUSION MATRIX

To assess the effectiveness of the fitness classification models, a confusion matrix is generated for each machine learning algorithm used in the system. The confusion matrix provides a detailed evaluation of correctly and incorrectly classified fitness levels, helping to analyse misclassification trends. Metrics such as accuracy, precision, recall, and F1-score are derived from the confusion matrix to measure the overall model performance. A comparative analysis of confusion matrices across different models, including Support Vector Machine (SVM) and K-Nearest Neighbors (K-NN), helps identify challenges in fitness level classification and highlights areas for improvement. By evaluating classification results through these metrics, the study aims to determine the most effective model for predicting user fitness while balancing computational efficiency and accuracy. Additionally, analyzing false positives and false negatives helps in understanding classification errors and model biases. Further, optimizing feature selection, hyperparameters, and data preprocessing techniques can enhance classification performance, leading to more accurate and personalized fitness recommendations.

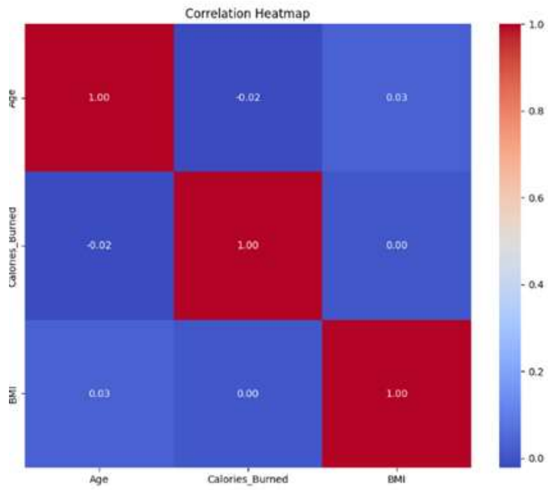

Fig 6: Details of Confusion Matrix

IX. RESULT & DISCUSSION

The experiments for the fitness analyzer application were conducted using two machine learning models: Support Vector Machine (SVM) and K-Nearest Neighbors (K-NN). The dataset, comprising 7,356 samples of user fitness data was split into two configurations for training and testing: a 70:30 split and an 80:20 split. Both models were trained and evaluated to determine their efficiency in classifying users into three categories: *Fit*, *Moderate*, and *Needs Improvement*. The performance of the models was assessed using a confusion matrix, which evaluates True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). These metrics were crucial in calculating performance indicators. Accuracy measured the proportion of correctly classified samples, while precision and recall provided deeper insights into the models' performance across different fitness levels. The F1-score, which is the harmonic mean of precision and recall, was particularly useful in evaluating how well the models balanced the trade-off between false positives and false negatives.

From the experimental results, SVM demonstrated strong classification performance, particularly when using a linear kernel to identify optimal decision boundaries between different fitness categories. The SVM model achieved an accuracy of 81% with the 70:30 split and 84% with the 80:20 split. On the other hand, K-NN, with an optimized k-value of 5, achieved comparable results with an accuracy of 79% for the 70:30 split and 82% for the 80:20 split. While SVM slightly outperformed K-NN in terms of overall accuracy, K-NN showed better performance in specific cases where the data distribution was more complex, highlighting its strength in handling non-linear relationships between features. The results highlight the importance of selecting appropriate features and tuning model parameters to optimize performance. Future work could explore the integration of ensemble techniques or deep learning models to further enhance classification accuracy and robustness.

Fig 7: Fitness analysis result

Analysis page

Analysis:0.7966438

accuracy :1.98643

macro avg :1.72%

Fig 8: Analysis Accuracy details

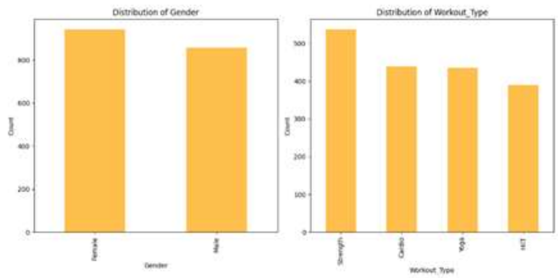

Fig 9: Distribution of Gender and workout type

Plot page

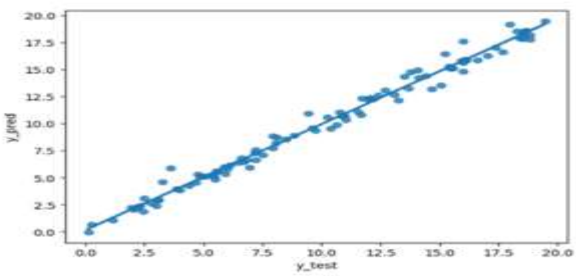

Fig 10: Scatter Plot of Test and Trained dataset

X. CONCLUSION & FUTURE WORK

This project presents an innovative approach to fitness level classification using user activity data from wearable devices. The proposed system employs two machine learning models—Support Vector Machine (SVM) and K-Nearest Neighbors (K-NN)—to predict and classify users into fitness categories such as *Fit*, *Moderate*, and *Needs Improvement*. The models were trained and evaluated on a dataset containing diverse features, including steps taken, calories burned, distance travelled, active minutes, sleep duration, heart rate averages, and body fat percentage. The performance evaluation, based on metrics such as accuracy, precision, recall, and F1-score, revealed that SVM achieved the highest accuracy at 84%, followed closely by K-NN at 82%.

The results highlight the effectiveness of both SVM and K-NN in accurately classifying fitness levels. These findings suggest that the combination of appropriate feature selection and model optimization can significantly enhance the accuracy of fitness classification systems.

For future work, the focus will be on expanding the dataset to include more diverse user profiles and additional features such as dietary habits, hydration levels, and stress indicators. Furthermore, the integration of real-time data streaming from wearable devices will be explored to enhance the system's adaptability and responsiveness. The use of ensemble methods and deep learning models like Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks will also be considered to improve the system's predictive capabilities. Lastly, personalized fitness recommendations based on individual analysis will be incorporated to offer more tailored health insights, contributing to a more comprehensive fitness management tool.

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