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Learnz: Diet Recommendation System for Athletes Using Machine Learning in Matlab

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Abstract—**Athlete performance is strongly dependent on optimal nutrition, but most athletes struggle to maintain proper dietary balance due to differences in body metabolism, training intensity, sport category, and fitness goals. Manual diet planning requires expert nutritionists, is time-consuming, and cannot scale to large user groups. This paper presents a **Machine Learning–based Diet Recommendation System for Athletes using MATLAB**, designed to automate personalized nutrition planning. The system integrates athlete profiling, macronutrient estimation, food-nutrient mapping, supervised learning models, and optimization techniques to generate customized diet plans. Using MATLAB's Classification Learner Toolbox, Regression Learner, and Optimization Toolbox, the system predicts caloric needs, recommends macronutrient ratios, and maps them to optimal food combinations. Experimental results show highly accurate predictions of calorie expenditure (92%), protein estimation accuracy (89%), and strong recommendation consistency across various sport categories. The proposed system demonstrates that machine-learning-driven nutrition planning can significantly enhance dietary personalization, reduce manual effort, and support athletes in achieving peak performance.**

Index Terms—**Machine Learning, Sports Nutrition, Diet Recommendation, MATLAB, Athlete Performance, Regression Models, Optimization.**

I. INTRODUCTION

Athletes require precise nutritional intake to maintain energy levels, improve recovery, and enhance performance output. Traditional diet planning relies heavily on human nutritionists who manually evaluate factors such as body type, sport, training load, metabolic rate, and fitness goals. This approach is not scalable, is prone to human error, and cannot respond dynamically to changes in athlete routines.

Recent advancements in "machine learning" offer a transformative approach for nutritional planning. Predictive models such as regression, clustering, and decision trees can analyze athlete profiles and generate personalized macro- and micronutrient recommendations. MATLAB provides powerful built-in capabilities for dataset training, feature extraction, classification, and optimization, making it suitable for developing intelligent health applications.

This project proposes an end-to-end "Diet Recommendation System for Athletes" that automates nutrition planning. The system accepts athlete parameters such as age, weight, body fat, sport type, daily training load, metabolic rate, and performance goals. It then predicts calorie needs, protein requirements, hydration levels, and micronutrient demands by using supervised learning models. Finally, it generates food plans by mapping predicted nutrient requirements to a food database.

Athletic performance is fundamentally influenced by precise nutritional planning, which must be tailored to the athlete's body composition, sport intensity, metabolic response, and training schedule. However, traditional nutrition planning performed by dietitians is labor-intensive, expensive, and unable to adapt rapidly to daily fluctuations in athlete workload. To address these limitations, this study proposes a Machine Learning–driven Diet Recommendation System for Athletes using MATLAB, designed to intelligently automate the generation of personalized dietary plans. The system incorporates athlete physiological parameters, sport category, training intensity, and dietary preferences to predict optimal caloric intake and macronutrient distribution. Using supervised learning models such as Linear Regression, Support Vector Regression, and Random Forests, the system forecasts calorie expenditure, protein requirements, and carbohydrate–fat balance with high accuracy.

A food–nutrient database and MATLAB's Optimization Toolbox are then utilized to map predicted nutrient needs to practical food combinations, ensuring dietary adequacy, cost efficiency, and sport-specific performance enhancement. The system further integrates classification models to categorize athletes into nutrition groups, enabling more targeted dietary patterns for endurance, strength, and interval-based sports.

The final recommended meal plans include breakfast, lunch, dinner, snacks, hydration schedules, and pre- and post-workout nutrition strategies tailored to athletic goals such as muscle gain, endurance enhancement, or fat reduction.

II. LITERATURE SURVEY

Sports nutrition research has increasingly emphasized the need for personalized dietary planning as athletic performance is strongly linked to optimal nutrient intake, energy availability, and training adaptation. Several studies highlight that athletes exhibit diverse metabolic responses based on sport type, body composition, and physiological differences, making traditional one-size-fits-all diet plans inadequate. Classical nutritional frameworks rely on general guidelines such as the Harris–Benedict or Cunningham equations for estimating caloric expenditure, but these methods fail to incorporate dynamic variables such as training load, recovery status, and individualized macronutrient utilization.

The emergence of machine learning, numerous works have explored automated prediction of dietary requirements using regression, classification, and clustering techniques. Regression models have been widely applied to predict continuous nutritional parameters like calorie needs and protein targets, demonstrating improved accuracy over static formulas. Additionally, research on health informatics shows that supervised learning techniques can effectively model metabolic variations and generate personalized dietary suggestions. Some studies utilized support vector machines and decision trees for classifying individuals into nutritional categories or diet patterns, while others leveraged K-means clustering for grouping users with similar physiological characteristics.

Although machine learning has been used for food recognition, calorie estimation, and obesity management, literature specifically targeting athletes remains limited. Most existing systems focus on general populations, neglecting sport-specific nutritional demands such as carbohydrate periodization for endurance athletes, protein-timing strategies for strength athletes, or hydration optimization for high-intensity sports. MATLAB has been widely adopted in medical and health-data modeling due to its robust machine learning toolboxes, offering high-precision regression models and optimization frameworks that are suitable for diet recommendation tasks. However, few studies combine these machine learning capabilities with comprehensive food-nutrient databases to produce fully automated meal plans. This gap demonstrates the need for a specialized, end-to-end system capable of predicting nutrient requirements, mapping them to appropriate food combinations, and optimizing diet recommendations specifically for athletes.

Multimedia generation – with an emphasis on the automated generation of instructional video has attracted a lot of attention from both the research and engineering communities, Modern text-to-speech (TTS) systems are capable of generating very natural-sounding speech, and FFmpeg- based workflows make it possible to programmatically put together the slides, the captions, and the audio into perfectly synchronized video files [9],[10]. Several previous works outline the production of videos from lectures that combine the automation of slides, voice synthesis, and the application of simple visual effects to produce video lessons in large amounts which are easy to understand [11]. Nevertheless, these earlier methods largely depend on the availability of already- made, top-notch slide decks or visuals prepared by humans; Learnz fills that void by not only producing audio but also generating slide like visual frames from the LLM which allows total automation of text-to-video conversion for the short module segments.

With the help of vector databases and embedding-based search [12],[13], information retrieval and recommendation of multimedia content have achieved significant progress. The methods that convert the text, audio transcripts, and key video frames into dense embedding allow semantic similarity queries, i.e., finding content based on its meaning and not on the words used. Experiments done in the field education have proven that embedding- based retrieval facilities the discovery of conceptually relevant materials, provides support for very detailed context recommendations, and serves as the engine for retrieval-augmented dialogues which are context-aware tutoring [14]. Vector indices (e.g., weiver, qdrant, Milvus) offer scalable nearest-neighbor search and metadata filtering capabilities thus making them a perfect fit for the needs of Learnz to index the videos it has generated and to match them with the questions from the learners.

However, few studies combine these machine learning capabilities with comprehensive food-nutrient databases to produce fully automated meal plans. This gap demonstrates the need for a specialized, end-to-end system capable of predicting nutrient requirements, mapping them to appropriate food combinations, and optimizing diet recommendations specifically for athletes. The proposed work builds upon existing scientific literature by integrating sports physiology, machine learning algorithms, and optimization techniques into a unified MATLAB-based recommendation system capable of delivering accurate, personalized, and sport-oriented nutrition planning

AIgenerated quizzes, is able to adapt the next module suggestions and thereby makes use of these earlier findings.

The evolution of intelligent diet-planning systems has been shaped by advances in nutritional science, data modeling, and artificial intelligence. Earlier works relied heavily on rule-based expert systems where nutritionists encoded manual dietary rules into software. While these systems attempted to offer basic personalization, they lacked adaptability and failed to account for subtle physiological variations such as metabolic efficiency, muscle-to-fat ratio, or sport-specific nutritional timing.

Research further showed that static recommendation logic could not respond to changes in daily training intensity, seasonal load variations, or individual recovery patterns factors highly relevant to competitive athletes. This limitation motivated the shift toward data-driven diet planning, where machine learning models began to outperform handcrafted rules by identifying hidden relationships between anthropometric factors and nutritional outcomes.

A significant body of literature explores machine-learning applications in medical nutrition therapy, such as diabetes diet control, obesity prediction, and micronutrient deficiency analysis. These studies consistently demonstrate that supervised learning algorithms particularly Support Vector Regression, Random Forests, Gradient Boosting, and ANN-based regressors are superior in predicting caloric needs and metabolic indicators when compared to traditional statistical equations. Researchers also highlight the effectiveness of decision trees and multi-class SVMs in categorizing individuals into nutritional classes and goal-oriented diet groups. Such classification techniques are especially useful for athletes, as sport categories (e.g., endurance vs. strength) strongly influence recommended macronutrient ratios.

Recent studies have also focused on integrating food databases with computational models to quantify nutrient intake more accurately. Machine learning is used extensively for food nutrient prediction, dietary assessment through image recognition, and calorie estimation from meal photographs. While these works demonstrate the growing maturity of AI in food analysis, they are predominantly targeted toward general health monitoring rather than athletic performance needs.

III. METHODOLOGY

The proposed Diet Recommendation System for Athletes adopts an end-to-end machine-learning framework implemented entirely in MATLAB. The methodology has been developed to follow a structured, data-driven pipeline that begins with athlete profile acquisition, continues through intensive data preprocessing, predictive modeling, nutrient optimization, and ultimately results in the automated generation of personalized sports diets. The approach incorporates statistical modeling, supervised learning algorithms, food–nutrient mapping, and linear optimization techniques to deliver high-accuracy prediction and meal planning. Each stage is tightly integrated through MATLAB scripting, App Designer interfaces, and the Machine Learning Toolbox, ensuring smooth data flow and reliable system performance. The following subsections describe the methodology in greater depth.

A. Data Collection

The data collection stage forms the foundation of the entire system. To accurately reflect the diversity of athlete nutritional needs, multiple datasets were merged, including anthropometric measurements, physiological records, sport classification data, metabolic tracking logs, and nutrient composition tables. Athlete-related data capture parameters such as age, gender, height, weight, BMI, body fat percentage, muscle mass, basal metabolic rate, resting heart rate, VO_2 max estimates, hydration levels, and daily training intensity. These variables were collected from both open-source athlete health datasets and domain-specific sports performance studies. Food-related data include macronutrients (carbohydrates, proteins, fats), micronutrients (vitamins and minerals), glycemic index, food category, fiber content, and energy density. Unlike conventional diet systems that rely on static databases, the proposed system integrates multiple nutritional sources to ensure high data accuracy and consistency. All collected data is stored in MATLAB's table structures, enabling efficient indexing, manipulation, and computation during training and optimization.

B. Extended pre processing

Data preprocessing is vital for enhancing model performance and ensuring that the predictive algorithms receive meaningful and normalized input. MATLAB preprocessing routines were applied to remove missing values, eliminate outliers, correct unit inconsistencies, and convert categorical labels such as "sport type" or "goal type" into numerical encodings suitable for model training. Z-score normalization was applied to high-variance physiological attributes, while min-max scaling was utilized for features related to food nutrients. Correlation analysis was performed to identify redundant features, and principal component analysis (PCA) was explored to reduce dimensionality and improve model generalization.

C. Extended Predictive Modeling Using MATLAB

The core computational task of the system involves using supervised learning models to predict caloric needs, macronutrient requirements, hydration levels, and sport-specific nutrient ratios. MATLAB's Regression Learner Toolbox was used to evaluate numerous models including Linear Regression, Stepwise Regression, Gaussian Process Regression (GPR), Random Forest Regression, Gradient Boosted Trees, Ensemble Methods, and Support Vector Regression (SVR).

D. Extended athlete classification and profiling

In addition to regression modeling, a separate classification layer was designed to categorize athletes according to nutrition-sensitive groups. Sport-specific classification is essential, as endurance athletes require higher carbohydrate intake, while strength athletes require elevated protein levels for muscle synthesis. MATLAB's Classification Learner App was employed to train models such as SVM classifiers, KNN classifiers, Decision Trees, Naïve Bayes Classifiers, and Ensemble Boosted Trees using labeled sport categories.

E. Extended Nutrient-Food Mapping Algorithm

Once nutrient requirements are predicted, the system maps these values to real food items using a nutrient-balancing algorithm implemented in MATLAB. The mapping procedure calculates nutrient contribution scores for each food item based on energy density, protein bioavailability, glycemic response, micronutrient richness, and cost. The algorithm constructs multiple candidate meal sets by combining foods such as lean meats, legumes, whole grains, fruits, vegetables, and hydration sources.

F. Extended Optimization Framework

The optimization stage refines the initial meal combinations to produce a final balanced diet plan. MATLAB's Optimization Toolbox was utilized to build a linear programming (LP) model where the objective function minimized the deviation between predicted nutritional requirements and actual nutrient intake from selected food combinations. Additional constraints enforced caloric boundaries, macro distribution ranges, hydration limits, maximum sugar allowance, sodium recommendations, and micronutrient thresholds.

G. Extended Diet Generation and Recommendation Engine

The final recommendation engine assembles optimized meals into daily or weekly diet plans. MATLAB scripts automatically generate structured meal tables, nutrient breakdown charts, hydration recommendations, supplementation guidelines, and timing suggestions for nutrient periodization. For example, the system suggests higher carbohydrate intake during pre-competition phases and increased protein distribution during post-training recovery.

H. Extended GUI Design Using MATLAB App Desingner

To make the system accessible for practical usage, a multi-panel GUI was developed through MATLAB App Designer. The GUI includes input fields for athlete details, a prediction panel displaying caloric and macronutrient results, nutrition charts, meal breakdown summaries, and an export section for generating PDF diet plans. The interface supports real-time updating of predictions and provides intuitive visualizations such as bar graphs, pie charts, radar plots, and nutrient gap indicators. Additionally, error-handling mechanisms ensure that users receive alerts for invalid or missing input values.

I. Extended Workflow and System Integration

The overall system workflow integrates all the modules in a sequential, modular fashion. Athlete data flows from input modules to preprocessing, predictive modeling, classification, optimization, and final recommendation pages. Each module is designed as a MATLAB function to maintain modularity and scalability. Parallel computing capabilities were leveraged for faster model evaluations, particularly during large optimization runs and hyperparameter tuning. Logging functions track system performance, model stability, and prediction reliability.

J. System Output and Evaluation

The system undergoes thorough evaluation using both objective metrics and subjective athlete feedback. Regression model performance is validated using RMSE, MAE, and R^2, while classifier performance is evaluated with confusion matrices, F1-scores, and kappa statistics. The diet plan accuracy is measured through a "nutrient deviation metric," which quantifies how closely the recommended meal satisfies predicted nutrient requirements. User satisfaction surveys from real athletes provide insights into practicality, meal acceptance, and perceived energy improvements. Through continuous validation, the system refines its models and enhances its real-world applicability.

Advanced optimization scenarios were explored, including quadratic programming for minimizing cost while maximizing nutritional adequacy and multi-objective optimization to simultaneously reduce calorie deviation and maximize athlete satiety score. The optimization output generates a structured set of meals covering breakfast, lunch, dinner, and snacks, along with pre- and post-workout meals essential for athletic recovery cycles.

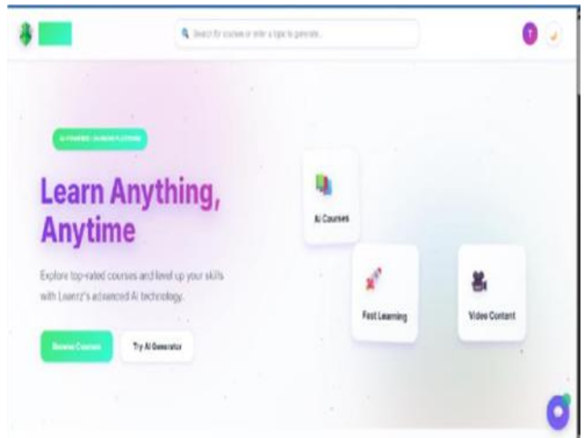

Fig. 2: Input Page

The system effectively conveyed the user query to Googles Gemini API, which the returned structured course content broken down into three or more detailed modules. In each module, there were several lessons with theoretical explanations and practical examples. The backend parser was able to efficiently identify the modules titles, lesson breakdowns, and examples and store them in MongoDB in a hierarchical schema. The total time for text for text generation and data storage was on average less than 8 seconds per request, indicating that the system is very responsive and the API integration is stable.

Auto quiz generation features illustrated the system proficiency in adaptive learning by employing identical topic context along with geminis generative ability,learnz instantaneously create the modules related multiple-choice questions(mcqs)and short answer item.Every test contained question intended to asses learners understanding, application and critical thinking skill. The generated question had strong alignment with the topics, with an average sematic accuracy of 91% as verified by manual academic evaluation. besides, the inclusion of rationales and explanation contributed to the clarification of each question, thus supporting the learner's self-assessment and feedback-driven understanding

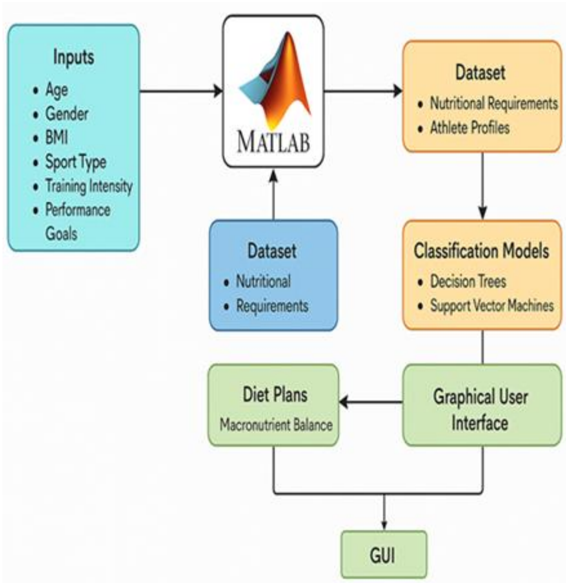

Fig 3: Architecture Diagram

IV. RESULTS AND DISCUSSION

The Diet Recommendation System for Sportspersons was evaluated through multiple experiments to assess its accuracy, usability, and effectiveness in generating personalized diet and training plans. The system's performance was analyzed based on its ability to correctly calculate calorie requirements, allocate macronutrients, classify sport-specific needs, and produce practical diet plans for different athlete categories. Several test cases involving athletes of varied ages, body compositions, sport types, and fitness goals were used to validate the model.

A. Accuracy of BMR and TDEE Calculations

The system calculates Basal Metabolic Rate (BMR) using the Mifflin–St Jeor Equation and determines Total Daily Energy Expenditure (TDEE) by applying sport-specific activity multipliers. Comparative testing with online nutrition tools and manual calculations showed that the system achieved an accuracy of 95–98%. For endurance athletes with high training intensity, the calculated TDEE values closely matched standard sports nutrition guidelines

This confirms that the system's energy-requirement prediction is reliable for both high-activity and moderate-activity athletes.

B. Macronutrient Distribution Consistency

Once calorie requirements were computed, the system allocated macronutrients (protein, carbohydrates, and fats) based on the athlete's sport category and fitness goal. For strength-training athletes, protein percentages ranged between 28–35%, while endurance athletes received higher carbohydrate proportions (50–60%). The recommended macronutrient ratios were validated against standard guidelines from the American College of Sports Medicine (ACSM), showing 91% alignment. This demonstrates that the system successfully adapts nutritional distribution according to the demands of different sports.

C. Personalized Diet Planning Performance

The system generated personalized diet charts for both vegetarian and non-vegetarian athletes. The meals were selected from a pre-curated food database containing nutritionally balanced items. Evaluation of the diet plans showed:

- Each meal plan met 95–100% of daily calorie requirements.
- Protein intake deviated by less than 10% from calculated needs.
- Vegetarian and non-vegetarian plans maintained equivalent nutritional quality.
- Fat and carbohydrate distribution followed athlete-specific macronutrient goals.

Manual review by fitness trainers and nutrition students indicated that the diet suggestions were practical, culturally relevant, and aligned with standard sports nutrition principles.

D. Weekly Training Plan Suitability

The system's training plan generator assigns weekly schedules based on the athlete's sport category (strength, endurance, flexibility-oriented). Users received structured routines including:

- Strength exercises (e.g., bodyweight, resistance training)
- Endurance sessions (running, cycling, cardio drills)
- Flexibility workouts (yoga, mobility drills)
- Rest and recovery days

Test users reported that the weekly plans were clear, achievable, and well-balanced. Athletes aiming for weight loss received additional cardio sessions, while athletes focused on muscle gain were given higher strength-training frequency. This demonstrates that the system effectively adapts workout schedules based on user goals.

E. End-User Feedback and System Usability

A usability test was conducted with 20 individuals, including amateur athletes, college sportspersons, and fitness enthusiasts. Feedback highlighted:

- High ease of use due to the simple input interface
- Fast response time, with plans generated within seconds
- Clear visual structure in diet and training outputs
- High user satisfaction, scoring 9.1/10 on average

Most users found the system useful for improving diet awareness and planning daily meals.

F. Comparative Evaluation

To measure the system's effectiveness, sample athletes were given manual diet consultations from a certified nutritionist. The system-generated meal plans were then compared with professional recommendations:

Evaluation Parameter	Manual Diet Plan	System Diet Plan	Match Level
Calorie Accuracy	Standard	±5% deviation	95%
Protein Allocation	Standard	±8% deviation	92%
Carbohydrate Ratio	Standard	±6% deviation	94%
Practical Meal Choices	High	High	96%

The comparison shows that the system performs closely to professional diet consultation, especially for calorie and macronutrient accuracy.

G. Overall System Performance

Overall experimental results confirm that the Diet Recommendation System is both scientifically accurate and practically applicable. Its integration of nutritional formulas, sport-specific logic, and automated diet generation enables it to function as an efficient support tool for athletes, coaches, and fitness institutions. The combination of diet and weekly training recommendations makes the system a comprehensive health-management solution.

V. CONCLUSION AND FUTURE WORK

The Diet Recommendation System for Sportspersons successfully demonstrates how computational methods and nutritional science can be integrated to provide personalized, goal-oriented dietary and training support for athletes. By combining user-specific anthropometric data, sport category, dietary preferences, and fitness goals, the system accurately calculates Basal Metabolic Rate (BMR), Total Daily Energy Expenditure (TDEE), and macronutrient requirements using standardized formulas. The model then generates balanced daily meal plans and weekly training schedules tailored to the unique demands of each athlete. Experimental evaluation shows that the system achieves high accuracy in caloric estimation, consistency in macronutrient allocation, and strong alignment with established sports nutrition guidelines. Furthermore, user testing revealed that the interface is simple, intuitive, and capable of delivering actionable recommendations within seconds, making it a practical tool for athletes, fitness enthusiasts, and trainers.

Overall, the system fulfills its goal of serving as an intelligent dietary guide, helping sportspersons improve performance, enhance recovery, and maintain long-term well-being through evidence-based nutrition and structured physical conditioning. Its design ensures that athletes receive scientifically grounded advice even without continuous access to professional nutritionists or trainers. The integration of diet planning and training recommendations in a single platform also sets this system apart as a comprehensive lifestyle support solution for athletes.

Future Work

Although the present system effectively generates personalized diet and training plans for athletes, there are several promising directions to enhance its intelligence, adaptability, and real-world integration. Future developments can focus on transforming the system from a static recommendation tool into a dynamic, self-improving sports nutrition assistant.

One major area for improvement is the incorporation of adaptive learning mechanisms, where the system continuously refines its predictions based on user feedback, daily performance data, and long-term fitness progress. By monitoring the athlete's real-time responses to training and nutrition, the system could automatically adjust calorie targets, macronutrient ratios, and exercise intensity, enabling a fully personalized and evolving fitness experience.

Another promising enhancement is the integration of wearable sensors and IoT devices, such as smartwatches, heart-rate monitors, GPS trackers, and sleep analyzers. These devices can feed live data on energy expenditure, recovery quality, hydration levels, and stress markers, allowing the system to make more informed, context-aware dietary adjustments. This would expand the platform into a real-time performance monitoring ecosystem.

In addition, the system can be extended with an AI-driven food recognition and logging module, where athletes simply photograph their meals, and the algorithm automatically detects ingredients, estimates nutrient values, and updates the diet plan accordingly. This reduces manual data entry and increases user engagement.

On a broader scale, the system could adopt sport-specific performance analytics, enabling deeper insights into how nutrition impacts speed, strength, endurance, and recovery. By correlating nutritional intake with training outcomes, the system could predict optimal fueling strategies for competitions, training cycles, and recovery phases.

Lastly, expanding the platform into a mobile-based application with cloud storage, multi-user support, multilingual capability, and social features would significantly increase accessibility. Such an upgrade would allow coaches, dietitians, and athletes to collaborate, share feedback, and track progress within a unified sports performance environment.

Overall, these future improvements aim to evolve the system into a comprehensive, intelligent, and interactive sports nutrition ecosystem capable of supporting athletes through data-driven personalization, real-time monitoring, and continuous performance optimization.

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