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Itgalpura, Rajankunte, Yelahanka, Bengaluru – 560064

NUTRIGUIDE: AI – POWERED NUTRITION PLANNING PLATFORM FOR ATHLETES IN DEVELOPING REGIONS

A PROJECT REPORT

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PRESIDENCY SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

Certified that this report "NutriGuide: AI – Powered Nutrition Planning Platform For Athletes In Developing Regions" is a bonafide work of "Syed Abdullah Hussaini (20221CIT0034), Harshavardhan (20221CIT0069), Shrisha Jamakhandikar (20221CIT0127)", who have successfully carried out the project work and submitted the report for partial fulfilment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in COMPUTER SCIENCE AND ENGINEERING, INTERNET OF THINGS during 2025-26.

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DECLARATION

We the students of final year B.Tech in COMPUTER SCIENCE AND ENGINEERING, INTERNET OF THINGS at Presidency University, Bengaluru, named Syed Abdullah Hussaini, Harshavardhan, Shrisha Jamakhandikar, hereby declare that the project work titled "NutriGuide: AI – Powered Nutrition Planning Platform For Athletes In Developing Regions" has been independently carried out by us and submitted in partial fulfilment for the award of the degree of B.Tech in COMPUTER SCIENCE ENGINEERING, INTERNET OF THINGS during the academic year of 2025-26. Further, the matter embodied in the project has not been submitted previously by anybody for the award of any Degree or Diploma to any other institution.

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ABSTRACT

This project presents NutriGuide, an AI-powered nutrition planning platform designed to deliver affordable, adaptive, and evidence-based dietary guidance to athletes in developing regions. The system addresses critical challenges such as limited access to professional dieticians, lack of sport-specific nutrition personalization, and the absence of dynamic diet–training synchronization in current fitness applications.

NutriGuide combines machine learning models, mobile-based user interaction, and sports nutrition databases to generate personalized diet plans tailored to the athlete's age, sport type, training load, and physiological parameters. The system integrates data from nutrition APIs and WHO/IOC guidelines to ensure scientific validity while enabling adaptive AI-driven recommendations.

The architecture comprises a React.js front-end, Node.js backend connected through a Supabase interface and database. The platform operates under a freemium model, providing essential features free of cost and offering premium options for advanced analytics, training synchronization, and wearable integration.

Model validation using a synthetic athlete dataset achieved an accuracy of 84.2%, with 82.6% precision and 80.8% recall in macro-nutrient balance prediction. The platform demonstrated 60% faster meal planning compared to manual diet chart creation and improved athlete satisfaction by 45% in pilot usability trials.

NutriGuide contributes to SDG 2 (Zero Hunger) and SDG 3 (Good Health and Well-Being) by promoting nutrition accessibility, awareness, and sustainable dietary habits.

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ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
API	Application Programming Interface
CDN	Content Delivery Network
CSV	Comma Separated Values
DB	Database
HTML	HyperText Markup Language
IFF	Identification of Friend or Foe
InfluxDB	Time-Series Database
IOC	International Olympic Committee
JSON	JavaScript Object Notation
JWT	JSON Web Token
ML	Machine Learning
NLP	Natural Language Processing
QoS	Quality of Service
REST	Representational State Transfer
RF	Random Forest
SDG	Sustainable Development Goal
SDK	Software Development Kit
SQLite	Structured Query Language Lite
SVM	Support Vector Machine
TF	Tensor Flow
UI	User Interface
URL	Uniform Resource Locator
UX	User Experience
WHO	World Health Organization

CHAPTER 1

INTRODUCTION

There have been growing challenges in ensuring the best nutrition and performance rates of athletes especially in developing countries due to the constraints of traditional mechanisms in planning diets. Current manual or generic interventions that are based on basic calorie counting or a single-size-fits-all to meal charting lead to poor compliance and nutrient imbalances (1525 per cent variation between target ratios of macronaturals) and an inability to align to training load or recovery patterns. The need to provide athletes with digital nutrition support systems is particularly highlighted by the recent reviews by the World Health Organization (WHO) and the International Olympic Committee (IOC), which are based on the idea of AI-driven personalization, mobile accessibility, and data-driven decision making, aims at achieving better performance and well-being. NutriGuide is an age-old case of AI in food planning based on automated, responsive, and easy meal planning that is formed according to the type of athlete, their body type, the intensity of training, and the level of recovery. NutriGuide supports evidence-based nutrition by integrating the concepts of artificial intelligence (AI), machine learning (ML) and cloud based application programming interfaces to replace the stagnant dietary guidance with dynamic and evidence-based information and solutions to assist athletes to reach their sustainable nutrition results in addition to tackling barriers of cost and accessibility.

1.1 Background

Sports nutrition is central in the issue of better physical performance, faster recovery, and inhibition of fatigue or injury. Nevertheless, in developing parts, most athletes have no access to certified nutritionists, personalized dieting plans, and monitoring of diets that correspond to performances. Traditional approaches usually require consulting the manuals or fixed instructions, according to which nutrition is prescribed with references to the overall energy needs; however, not the physiological and training data. Sport specificity, environmental and individual variations in metabolic rates in static diet charts and commercial fitness applications would lead to nutritional inefficiencies and lack of practice in adherence to diets. As reported by a 2023 review of Amawi et al. over 70 percent of non-elite athletes fail to consume appropriate protein or micronutrient amounts due to lack of individualised advice. Machine learning and artificial intelligence have offered a channel of individualized, statistical nutrition planning. AI models are able to predict optimal macro nutrient distribution, caloric index, and meal timing by analysing parameters like training load, dietary preferences, the availability of foods in the respective regions, and metabolic goals in a way that keeps changing in relation to the changing schedule of the distinct athlete. Such systems are now possible and scalable with the development of cloud computing, nutrition databases (e.g., Edamam, Open Food Facts) and open-source AI systems like TensorFlow and Scikit-learn. Together with mobile-based interfaces (React.js, Node.js, FastAPI), NutriGuide provides the ability to serve an environment with resource constraints with elite-level nutrition calculation.

1.2 Statistics

Exponential growth in the global sports nutrition market is projected to rise to $81 b by 2030, but it is still extremely biased against the developed economies. Only under 10 per cent of athletes in developing areas use certified nutritional counselling or customized nutrition websites. The most notable facts that justify the creation of NutriGuide are:

- WHO (2024) estimates that more than 65% of athletes in South Asia and Sub-Saharan Africa do not reach the required minimum daily protein consumption because of the inability to think about it or do not have the means to get specific plans.

- DenizGarcia et al. (2023) in their study discovered that mHealth nutrition applications had a 20-30 per cent dietary compliance but did not include sport-specific personalization. - AI diet reconfigured to each individual displayed an enhanced time of performance recovery and 40 percent amplified emotionally to adherence in contrast to fixed plans (Wang et al., 2025).

- In general professional dieticians normally cost around 2000-5000 rupees a month and young sportspeople in developing economies cannot afford it. Freemium model of NutriGuide gives premium user scientific accuracy at NutriGuide premium model costs are the same at 300/month.

According to a survey conducted by sport academies in India and Kenya (2024), 80 thanks- to non-digital methods of meal planning are still used by 80-percent of participants in these surveys. According to global patterns, in 2030, more than 100 million users of AI-based nutrition planning platforms will exist, the biggest population of which will be comprised of athletes and fitness professionals. In the case of developing nations, these platforms might positively affect nutritional literacy and indirectly address SDG 2 (Zero Hunger) and SDG 3 (Good Health and Well-Being).

1.3 Prior Existing Technologies

There are a number of digital nutrition systems and diet-tracking applications already found on the international level; however, the majority of them have limitations in the context of individualization, accessibility, and integration. These technologies may be classified as commercial applications, academic research systems, open source frameworks and clinical decision support platforms.

Commercial Systems

Applications, including MyFitnessPal, Cronometer, and Yazio, contain large food database, caloric tracking features, and macronutrient calculators, which have an accuracy of about 85-90% in estimating the caloric intake and feature powerful usability. Nevertheless, they are mostly general-purpose, have not been designed to serve athletic communities, are prohibitively expensive to their users in less developed countries, are not connected to training programs, recovery indicators, or wearable sensor information, and do not support local foods or culturally sensitized eating habits. FitGenie and Heali represent the examples of AI-based diet apps that provide personalized advice but exist in closed ecosystems, thus, restricting the levels of customization and making them reliant on proprietary datasets.

Academic Research Systems

AI-based dietary guidance has already been researched on numerous prototypes. As an example, Wang et al. (2025) proved personalised dietary intervention on the basis of machine learning with a predictive score of 78 per cent in nutrient requirements, but Nogueira-Rio et al. (2024) combined wearables and AI to track caloric expenditure with statistically significant improvement in accuracy. However, these systems are still experimental and have not been implemented in large scale applications with large populations of athletes.

Open-Source Frameworks

Specialized APIs that provide nutrition and food detailed data include Edamam, Open Food Facts, and fooddata central; and can be used in tailored AI applications. Although they are flexible, high levels of technical expertise are needed to implement them, and the frameworks do not have high-level logic of personalization of athletes.

Clinical and Health Platforms: The clinical and health platforms comprise multiple sections such as nursing,Primary Care, Mental Health Services, Clinical Pediatrics, Clinical Oncology, Primary surgery, and Clinical surgery.Clinical and Health Platforms: The clinical and health platforms consist of various segments that include nursing,Primary Care, Mental Health Services, Clinical Pediatrics, Clinical Oncology, Primary surgery, and Clinical surgery.
The World Health Organization and International Olympic Committee have shared online nutrition models that are designed to help clinicians to prescribe performance and recovery diets. Yet, such systems are fixed and require operating by hand; moreover, they are oriented to clinical usage and not to constant involvement with an athlete.

Overall, there are numerous technologies that can be used to track and protect the diet, but none of them research, consider, and implement AI, sports science, and cost-efficiently to provide real-time nutrition and performance-based nutrition plans.

1.4 Proposed Approach

NutriGuide addressed these shortcomings by launching an AI-enhanced, modular, and scalable solution that is specially designed with athletes and fitness communities that can be deployed in resource-constrained environments, in mind.

There are four fundamental layers of the system architecture:

Data Acquisition and Profiling Layer

This layer is where the data acquisition and profiling functions are contained. Athletes enter personal information, such as age, gender, sport, body type, and goals, diet preferences and restrictions. The platform can also support inputs of training loads including length of duration, frequency and level and incorporates wearable to track activities.

AI-Powered Analytics and Recommendation Engine

The company has also established an artificial intelligence (AI) powered analytics engine, upgradeable to recommendation engine. The machine-learning engine, which is written in Python and uses TensorFlow and Scikit-learn, is generated based on meal recommendations by analysing.

- Macronutrient balance (protein, carbohydrate, fat ratio)
- Adequacy in the micronutrients (vitamins and minerals)
- Hydraulic needs and recovery needs.

A hybrid approach that uses the elements of a Random Forest and that of a Neural Network model predicts the personalized nutrient goals and the predictive performance of 84.2 per cent in validation experiments, run on noisy athlete data. The engine reacts to the user feedback and the intensity of the latest training by dynamically adjusting the plans, thus—it provides a coordinated nutrition-training association.

Backend and storage infrastructure

The node.js and express.js backed backend are used to interact with a MongoDB Atlas cloud database to allow the efficient retrieval and storage of data. The machine-learning engine is implemented as FastAPI microservice bearing predictions of models by way of RESTful APIs. JWT based authentication and TLS encryption ensures the safety of data and users, hence, remaining in line with the current data protection standards.

User Interaction Layer and Visualization Layer

The built user interface is designed with the help of React.js and Tailwind CSS and provides:

- Reliable and updateable nutrition reports.
- Daily meal recommendations
- Synchronization charts of training nutrition.
- Materials that are associated with Sustainable Development Goals (SDGs).
- Interactive learning games
- Interactive learning modules to promote in-the-long-term learning.

The design is modular to allow the further addition of new features including wearable device synchronization, automatic hydration reminders, and food affordability analysis.

1.5 Objectives

NutriGuide has specific, measurable, achievable, relevant and time bound (SMART) goals which are technical, social and operation based objectives.

Objective 1: Personalized AI-Powered Nutrition Planning.

An AI engine will be designed and developed that will create customized diets based on the athlete profiles, type of sport, and intensity of training.

Target model performance:

- Accuracy $\geq$ 80 %
- Precision $\geq$ 78 %
- Recall $\geq$ 75 %
- Mean response latency $\leq$ 200 ms.

Objective 2: Eliminate Training Loading and Nutrition asynchrony.

- Live modification of dietary advice will be possible based on training periods, rest status and sport energy system. Under integration of activity data on wearables (heart rate, number of steps, amount of calories burned) will be used to dynamically adjust macronutrient recommendations.

Objective 3: Provide Secure, Scalable Cloud Architecture.

- The backend will be hosted on a cloud platform that can support 1,000 or more active users at any given time with an average of less than 250ms of response time.
- The encryption of TLS 1.3, JWT authentication, and data anonymization will be done to secure user safety.

Objective 4: Design Educational and User-Friendly Interface.

- A smart dashboard that offers real time feedbacks on the form of calorie intake, nutrient balance and recovery planning will be created.
- Nutrition Awareness Module, which will be in accordance with SDG 2 and SDG 3, will provide gamified learning, tips and quizzes.
- The interface is going to be designed to ensure a response time of less than 150ms to the UI and a pilot-test response of 95% positive usability.

Objective 5: Be Cost-Effective and Accessible.

- The business model to be adopted will be a freemium business model that offers basic functionalities without any charge but advanced analytics at a reasonable cost.
- The 10,000 and more scalability of deployments will have low operations overhead.
- Through cost, affordability will be illustrated by the total development cost of the system of 15,000$, such that in the case of regional sports institution, they can adopt NutriGuide without any significant infrastructure cost development.

1.6 SDGs

It also influences a number of United Nations Sustainable Development Goals (SDGs) with the use of its technological potential, operational effects, and the benefit to society at large. Figure 1.1. shows the seventeen SDGs that were adopted in 2015 by all the UN members as a global call to action to peace and prosperity.

Fig 1.1 Sustainable development goals

SDG 2: Zero Hunger

NutriGuide has direct promotion to SDG 2 - Zero Hunger, giving priority to the elimination of hunger, achievement of food security, reduction of nutrition, and sustainable agricultural diversity. The platform is the solution to nutritional inequity as it democratises the provision of scientifically informed, AI-driven dietary advice to athletes in the developing world and in resource constrained areas. The geographical and economic barriers that would impede NutriGuide are removed through the use of freemium digital delivery mode that guarantees the low-income athletes access to customized nutrition guidance.

The meal recommendation application is AI-powered and relies on global/regional nutrition databases (WHO, IOC, Edamam) to design balanced and affordable diets by using locally purchased foods to create them, consequently establishing sustainable eating habits.

SDG 3: Good Health and Well-Being

NutriGuide has significant contribution towards SDG 3 -Good Health and Well-Being, which aims at ensuring healthy lives, and good health to all. The platform meets this goal through the combination of nutrition science, machine learning, and mobile access to give athletes dynamic dietary guidelines, which change cohesively with physical activity, recovery, and weather conditions.

The platform tackles the risk of fatigue, deficiency of nutrients, and performance related injuries linked with poor nutritional planning in form of personalised nutrition management. Through its recommendations on maintaining balanced intake of macronutrients, as well as, hydration, NutriGuide boosts the physical and mental health conditions of athletes, which in turn promotes their long-term health results.

Also, the site includes informative modules that develop nutrition literacy, combat false information, and promote sustainable eating habits within societal groups. NutriGuide, through making the health-oriented digital tools affordable and data-driven, will fulfill the principles of SDG 3 of universal access to knowledge and opportunity related to healthcare

SDG 9: Industry, Innovation and Infrastructure

Though a health-related project, NutriGuide proceeds to the SDG 9 Industry, Innovation and Infrastructure through the example of how affordable AI and digital technology can learn to innovate health and sports in developing markets. Technological inclusion of the project consists of the low-cost, scalable digital infrastructure that incorporates the open-source ecosystems (react.js, Node.js, Tensorflow, and MongoDB atlas) into a single environment.

This architecture favours local innovation as it allows developers in the region, institutions and sports academies to tailor and implement the platform with limited technical requirements. With a monthly per-user cost of less than 2-5 AI-drived personalization, NutriGuide demonstrates that high-quality nutrition analytics can be democratised with small sports clubs, schools, and programmes of non-elite athletes - all of which have historically not had access to such technologies. Its open, modular structure helps it to be interoperable encouraging capacity building locally and digital self-reliance in developing economies.

SDG 12: Responsible Consumption and Production

NutriGuide still helps to achieve SDG12 - Responsible Consumption and Production because it induces sustainable eating practices and minimized food waste by use of smart meal planning. With the help of the system, optimal dietary advice will be given based on the availability of foods during the season, the local agricultural products to be used, and the energy requirements of the specific individual ensuring that people use resources that are of less consumption.

Through offering nutritionally balanced meal options that are portion-controlled, NutriGuide can reduce over consumption and the high demand on processed foods or imported foods. The application contains educational modules that create awareness of the environmental impact of the food options, including their impact on environmental footprint, and thus encourage athletes to give preference to locally sourced and minimally processed food.

In addition, replacing the use of papers in nutrition tracking with the digital form of record keeping, NutriGuide also indirectly reduces the use of paper; it also helps create digital sustainability. Taken together, all of these practices represent the idea of sustainable resource management and a conscientious production consumption balance provided by SDG 12. Collectively, these practices embody the SDG 12 principles of sustainable resource management and conscious production-consumption balance.

SDG 17: Partnerships for the Goals

The implementation strategy of NutriGuide is inherently forward-looking the SDG 17 - Partnerships for the Goals, implying cooperation between academic institutions, non-governmental organisations, sports federations, as well as local health authorities. The project facilitates data dissemination, collaboration in the development, and unrestricted research in the field of sports nutrition in the developing regions.

With the combination of worldwide accepted databases (WHO/IOC nutrition databases, Open Food APIs) and locally available data on food composition, NutriGuide is one of the scalable approaches to global collaboration in digital health and AI ethics. These partnering environments support innovation, develop local digital capabilities, and facilitate worldwide development of equal access of sports nutrition knowledge.

1.7 Overview of project report

The report involves detailed documentation of the Nutriguide project including all the phases of the conceptualisation and the design to the implementation, testing, and evaluation. It also illustrates how the suggested system would combine the fields of artificial intelligence, sports nutrition science, and online availability to provide sportspeople in developing countries with the personalised diets.

- **Chapter 1** provides an introduction to the project to define its context, background and motivation. It identifies the issues with the availability of affordable and tailored nutrition planning to athletes and presents statistics that support its position, creating a picture of the lack of sports-specific nutrition support in developing countries. It should also be noted that the chapter examines and reviews extant nutrition and fitness applications, describes the limitations of such apps, outlines the proposed AI-powered Nutriguide application, defines concrete and measurable project objectives, and maps the contributions of the system to various United Nations Sustainable Development Goals (SDGs), including Zero Hunger and Good Health and Well-Being.

- **Chapter 2** includes a large literature search that reviews the existing scholarly studies and commercial applications relating to mobile health (mHealth) applications, AI-driven dietary interventions, and digital sports nutrition systems. The review summarises the outcomes of ten peer-reviewed journal articles and global research, pointing to gaps in research in current technologies, namely, the missing athlete-oriented personalisation and dynamic meal-training flexibility.

- **Chapter 3** represents the V-model approach that has been selected to develop the project, which will allow mapping the requirements collection, AI model creation, backend architecture, user interface design, implementation, and testing stages. This chapter clarifies how all the steps of the V-model make sure that a trace is maintained between the functional requirements, the algorithmic design and verification thus ensuring that the outputs of the system meet the original purposes in terms of accuracy, usability and performance.

- **Chapter 4** provides the project management structure, such as the entire Gantt-chart-based construction schedule of the requirement analysis process, design, implementation, integration, and testing. It includes as well a risk analysis of PESTEL, which examines political, economical, social, technological, environmental, and legal conditions that can affect digital health solutions in developing areas. The chapter ends in a cost benefit analysis and a resource allocation strategy, which proves the affordability and scalability of the project to educational institutions and sports organisations.

- **Chapter 5** is devoted to the system analysis and design, where functional, performance, and security requirements are provided. It contains functional block diagrams and system architecture diagrams, UML use-case models and data flow representations, which show the way data flows around the AI engine into recommendation output. Backend-frontend communicative models, API flow of communication, database (MongoDB), and integration with nutrition data sources, including the Edamam API and WHO/IOC datasets are also recorded in the chapter.

- **Chapter 6** captures the implementation step, which includes software components configuration and deployment of AI model. It gives specific details about the frontend and the backend integration, the training of AI models with Tensorflow and Scikit-learn, and the deployment of model inference with FastAPI microservices. In the chapter, the illustrative code segments, data preprocessing steps, and sample outputs obtained during the modeling testing and simulation are also provided.

- **Chapter 7** contains the evaluation and results with the description of how the testing is conducted, how the test-cases are designed, how the tests are validated and what performance results were achieved. It provides both quantitative (e.g. accuracy and precision of prediction and recall of nutrient recommendations) and qualitative (e.g. user feedback on pilot reviews) feedback. The chapter also compares the performance of Nutriguide to the strategies of the baseline, with descriptions of strengths and weaknesses and potential improvements. The social, legal, ethical, sustainability, and data-safety factors of the Nutriguide platform are discussed health data.

- **Chapter 8** It evaluates the social consequences of having equitable access to nutrition, adherence to the data-protection regulations like the Personal Data Protection Bill (India 2023), and principles of GDPR and its ethical implications concerning the disclosure of an algorithm and its fairness. The system will promote responsible consumption and data-inclusiveness among digital users, the features of sustainability will encompass, and data-safety will provide a secure storage and encryption of user health data.

- **Chapter 9** will put the report to an end by summarizing the development process of the Nutriguide project, the results attained in comparison to the outlined goals, and outlining the technological, social, and economic value of the platform in the management of nutrition athletes. It also proposes potential improvements in the future such as increased functionality with wearable devices, a range of different languages to reach more regions, more advanced reinforcement-learning-based meal optimisation, and potential collaboration with sports federations and non-governmental organisations to scale it to large scales.

CHAPTER 2
LITERATURE REVIEW

Substantial research interest has been generated in the past few years on the topic of the development and use of AI-based nutrition systems and the rise of mobile Health (mHealth) applications to provide dietary guidance. Therefore, this chapter will offer an extensive review of previous and current research that relates to mobile nutrition apps, sports nutrition recommendations, AI-supported diet personalization, wearable integration technologies, and other related technology applications. This review will summarize the findings of ten peer reviewed references and other authoritative references in order to identify the gaps in knowledge addressed by NutriGuide, which are listed below.

2.1 Mobile Nutrition and mHealth Applications

In a systematic review of machine-learning in nutrition research, Kirk et al. made a point about the ability of ML models to help in nutrition assessment, food recognition, and personalized nutritional advice [1]. Their discussion showed that it was possible to derive nutritional inferences based on user data, but their discussion was not a focus on the application deployment of their arguments to athletes, but on research pipelines. The limited availability of labeled data and a lack of investigation of deployment possibilities in low-resource environments are observed as the implementation barriers.

The article by Deniz-Garcia et al. [2] conducted a systematic review of the quality, usability and efficacy of mobile health (mHealth) nutrition applications. Their meta-analysis showed that app-based interventions could improve dieting behaviour, and the improvement in adherence rates was between 15 and 30, and the overall clinical outcome in non-specialized populations. However, the analyzed literature was heterogeneous as it concerned the design, and most applications focused on the general wellness instead of sport-specific performance. The review has pointed at the insufficient personalization of athletes and insufficient combination with training data.

Ferrara et al. [3] presented a narrow review of smartphone diet -tracking apps including MyFitnessPal and Cronometer with satisfactory usability and fair accuracy of foodenergy coding (about 8090 percent with typical foods). These do not, however, make a calorie-understanding of popular applications; they fail to modify the advice to suit the form of sport and/or the burden of training and the requirements of recovery. They also often need to be manually logged on food, which creates an inhibitory barrier to time-estressed athletes.

Gioia et al. [4] analyzed the mobile applications that track the timing and food intake patterns. The accuracy of capturing meal timing and circadian rhythms became known in their work, which allowed the research-grade data collection. Nevertheless, not many applications transform the timing data into practical and athlete-specific nutritional recommendations aimed to maximize the performance and the recovery.

Key observation: mHealth apps enhance compliance and data registration but do not have a sport-specific functionality to enhance the athlete performance with the necessary level of personalization and automatization.

2.2 Sports Nutrition Guidelines and Evidence

Based on the review of the literature on the core knowledge of sports nutrition, such as energy systems, macronutrient and micronutrient outlay, and timing strategies, Pramukova et al. [5] offer authoritative baseline facts on the nutritional requirements of endurance and strength athletes. Using evidence-based ranges and carbohydrate periodization principles, as well as recovery nutrition protocols, are provided in the literature.

Slater & Phillips [6] provided discipline-specific information on suitable strength athletes adding power, explaining macronutrient preparation, the time of pre- and after-training protein consumption, and the use of supplements. These are clinically strong but are stable guidelines devised to be assessed at a single time or by clinicians to execute, in the case of plans but not continuous and automated personalization.

Best-practice nutrition of elite athletes, including nutrient periodization, environmental adaptations and anti-doping considerations are compiled in IOC/Olympic resources [7]. Although authoritative, these resources need to be expertly translated into specific and context apposite prescriptions that can be applied to non-elite athletes and areas with low food diversity.

Key observation: Science of sports-nutrition offers a rule-book of recommendations; but it is fixed and clinical-aspect based, and requires dynamical, evidence-based algorithms that can be made universally available..

2.3 AI and Machine Learning for Dietary Personalization

The systematic review of the AI application in personalized nutrition interventions by Wang et al. [8] found that there is new evidence that ML can be used to personalize nutrition, thus enhancing the adherence and some aspects of metabolic phenotypes. Common ML problems were the prediction of intake platforms, food recognition through computer vision, and recommendation ranking. Reports of effectiveness were mixed, pilot systems only amassed modest improvements, but larger validation is yet to occur.

Nogueira-Rio et al. [9] have conducted a survey on mobile applications that combine AI and wearables to assist in nutrition management. Their results indicate that sensor data (heart rate, activity) used together with self-reports can give more precise estimates of energy-expenditure and individual recommendations. However, there are few end-to-end athlete real solutions in which the training cycles are synchronized with macros and meal timing.

Most recent ML experiments are training either an ensemble of methods (random forests, gradient boosting) or a deep network (Maersk tools LSTM) to predict nutrition based on plate appearances with an average predictive accuracy of 78-86 per cent on hand-selected validated data. The challenges are dataset size, label quality, and model interpretability which are important issues to clinician and athlete trust.

Key observation: AI is capable of personalization of diets however domain aligned feature engineering (training load, sport type, regional foods) is needed and explainable to make it adoptable into a sports scenario.

2.4 Wearables and Training–Nutrition Synchronization

The growing literature is evidence of the importance of training load synchronisation with nutrition when using writeable metrics. Research suggests that training stress and recovery state can be proxied by heart-rate variability, session RPE and accelerometry, which can be used to apply prompt nutrition changes (e.g. increased carbohydrates after high-load sessions), which increase recovery indices by 10-20 percent in short studies.

Yet, the vast majority of commercial wearable integrations focus on step counting and calorie strategy calculation; only a little of them relate these indicators to nutrition timing, or the adjustment of particular sports macronutrients. The issues with integration include the presence of heterogeneous sensor APIs, differences in accuracy between devices and the problem of battery/data-privacy limits.

Key observation: Wearables have a great context to adaptive nutrition, however, they do not have standardized integration layers and sport orthodox decision rules.

2.5 Food Composition Databases and API Ecosystem

Automated nutrient calculations Persist accessible nutrient data is available on open nutrition APIs like Edamam, Open Food Facts, and the USDA FoodData Central, which contain extensive information about the food composition. These databases are used to transform food items into macro/micronutrient values accurately averagely sufficient to be used in recommendation engines.

Its limitations are poor coverage of regional foods (traditional meals, local food ingredients), inconsistent standardization on portion size and random granularity of micronutrients. In case in deployments are made in developing areas, it is necessary to contribute localized food composition tables to world databases.

Key observation: Food databases are basic bricks but they need to be localized and adjusted to portions standards so that meal plans can be precisely prepared in a wide variety of settings.

2.6 User Experience, Behavioural Change and Gamification

According to the literature in behavioural science, digital interventions including goals, reminders, feedback, and gamification have better long-term adherence. The literature review indicates an enhancement of sustained use by 20 40 percent when apps are designed with social features, progress badges and micro-learning short modules.

The motivational driving forces in the population of athletes are different (performance results, coach feedback), and, therefore, customized user experience metaphors (training milestones, recovery scores) should be applied in lieu of generic wellness gamification.

Key observation: Having said that : binge on the user-experience: This can be facilitated more easily by design that facilitates ease toward athlete motivations and streams of work by coaches.

2.7 Privacy, Ethics and Regulatory Considerations

Technologies Applications used to manipulate health-related data will have to address data protection laws (e.g., GDPR) and jurisdiction. Some of the ethical issues include bias in algorithms (algos were trained on unrepresentative groups), black box recommendations, and unsafe advice based on AI without human audit (e.g., calorie deficits at severe levels). Reviews optimize the significance of explanations of the model, human-in-the-loop protection (nutritionist review of high-at-risk users), and explicit consent/opt-out protocols.

Key observation: Privacy-first-design, equity audits, and edge-case paths through clinicians ought to be viewed as the key to responsible deployment.

2.8 Evaluation Metrics and Benchmarking

Multidimensional assessment as suggested by Patel and Singh [10] and similar literature in the field of ML in health includes: classification accuracy to predict nutrient-risk, recall/precision in essential nutrient deficits, and compliance with the users and satisfaction with behavioural change. Accuracy The accuracy of Pilot AI diet systems usually range between 75% and 86% when performing tasks that involve macronutrient allocation, and the user satisfaction rates increase by approximately 3050% in short term pilots.

2.9 Summary of Literature Reviewed

Table 2.1 presents a comprehensive summary of the key findings, methodologies, and limitations identified in the reviewed literature.

Table 2.1 Summary of Literature Reviews

Reference	Focus Area	Key Findings	Performance / Impact	Limitations
Kirk et al. [1]	ML in Nutrition	Demonstrated ML feasibility for dietary inference	—	Research-oriented; limited deployment
Deniz-Garcia et al. [2]	mHealth effectiveness	Apps improve adherence (15–30%)	Behavioural gains	Generic apps; not sport-specific
Ferrara et al. [3]	Diet-tracking apps	Good usability; calorie coding ≈80–90%	High usability	Calorie-focused; lacks training sync
Gioia et al. [4]	Food timing apps	Accurate meal-timing capture	Research useful	Little prescriptive automation
Pramuková et al. [5]	Sports nutrition review	Foundational athlete nutrition guidance	—	Static; clinician dependent
Slater & Phillips [6]	Strength sports nutrition	Detailed macronutrient/timing protocols	—	Discipline specific; not automated

IOC resources [7]	Elite athlete guidelines	Authoritative best practice	—	Not algorithmic; needs translation
Wang et al. [8]	AI personalization review	AI tailors diets; promising pilots	75–85% model effectiveness in pilots	Small samples; limited large-scale trials
Nogueira-Rio et al. [9]	Apps + wearables	Integration improves energy estimates	Improved accuracy vs self-report	Few athlete-centric deployments
Patel & Singh [10]	ML evaluation in health	Recommends combined algorithmic & behaviour metrics	Guidance for evaluation	Need for standardized benchmarks

2.10 Identified Gaps and Research Opportunities

The literature review has shown that there are some significant gaps and opportunities to be filled by NutriGuide.

1. **Athlete-Specific Personalization Gap:** Those applications and prototypes of artificial-intelligence are mainly generic or clinical population-based. As a result of this, there is a rather significant demand to develop systems that integrate sport type, positional role, energy-system demands and periodized training cycles into meal-planning algorithms.
2. **Training–Nutrition Synchronization:** Very static nutrition to existing training load and recovery measures is hardly found. Combination of wearable equipment and training records to tune macro-timing and session-specific fueling, is a research enigma.

3. **Localization & Food Coverage:** International food databases are not fully covered in terms of regional food and portions, which is necessary in the developing regions when proper recommendations should be made. There is a need to carry out research on effective mechanisms on how to improve local food composition data.

4. **Interpretability & Clinical Safety:** Deep networks and other black-box models with high accuracy are hindered to adoption because of non-interpretability. This means an opportunity to explainable machine learning on nutrition (e.g. feature importance on macronutrients, rule-based fallbacks), as well as clinician-in-the-loop protection of high-risk users.

5. **Multi-Modal Data Fusion:** Such integration of self-reports, wearable feeds, environmental condition (heat, altitude), and food data in a roughly high bandwidth, low bandwidth sustainable pipeline is an outstanding research requirement.

6. **Long-Term Outcome Evidence:** Short-term increases in adherence are reported in most pilot studies; there are minimal randomized controlled trials that have associated AI-generated nutrition with performance, injury prevention, or growth measures.

7. **Accessibility & Cost-Effectiveness:** Proprietary systems that are based on commercial AIs can become expensive. They are required to have open and low-cost and scalable platforms, which can sustain performance without increasing overheads when deploying in resource-limited scenarios.

How Nutriguide Addresses These Gaps:

NutriGuide suggests a hybrid solution that will unify interpretable ensemble machine learning (Random Forest + Gradient Boosting) with heuristics in sports nutrition in the form of rules that will be developed based on the WHO/IOC guidelines, training synchronization through the inclusion of wearables, and a strategy of adding to the local food database. The service focuses on what can be explained, pathways to be reviewed by clinicians and freemium business to make the service available and scalable to the developing world.

CHAPTER 3
METHODOLOGY

In this chapter, the development of NutriGuide, an artificial-intelligence based nutrition planning platform, targeting athletes located in developing areas, is fully explicated using the methodology that was embraced to design the platform. The methodological framework consists of a set of steps, namely, the requirement analysis, system design, the data collection, the development of AI models, the implementation, the testing, and the validation, all these steps are necessary to establish traceability between the user requirements and the functionality, which has been deployed. It uses domain knowledge in the field of sports nutrition (IOE/WHO), in mobile engineering as well as AI/ML pipelines, and usability engineering, placing a strong focus on scalability and data privacy and low-resource feasibility.

3.1 Research Design

To fulfill the multidisciplinary nature of the project, NutriGuide takes the mixed-method research design approach, which combines both qualitative and quantitative research methods.

Qualitative phase: The phase included stakeholder interviews, including coaches, nutritionists, and athletes, a review of available IOC/WHO nutrition guidelines, and a usability benchmarking analysis of available generic mHealth apps (MyFitnessPal, Cronometer). The qualitative investigation distinguished the requirements of the users, namely training-nutrition synchronisation, localisation of the food within the region, and affordability, and constrained the acceptance requirements of the UI/UX and comprehension of the recommendations.

Quantitative phase: The quantitative investigation was on the generation of datasets (synthetic and pilot-collected), engineering of the features between training load (fuel consumption) and nutrient demands, and the training and hyper-parameter optimization of models and statistical validation of model predictions and user outcomes. Key experimental questions used: Do: Is it possible to get a ML engine to make predictions of athlete nutrient targets with at least 80 -percent accuracy? and Do: Does AI-based-planning increase adherence and recovery outcomes?

The general technical workflow focuses on having an ML centric mobile architecture: an ingested user input and a wearable data will be transformed into pre-process data, features will be extracted, and an ML inference (the recommendation engine) will be applied into generating recommendations which should in turn be provided with a feedback loop.

3.2 Data Collection

The synthetic dataset generation was combined with data collection and pilot-field data and external nutrition databases in building up a strong training and validation corpus.

1. Sources & modalities:

- User Profiles (moribund): age, sex, height, weight, sport category (endurance / strength / mixed), playing position, diet (veg/non -veg), allergies, socio-economic limitations, athletic baseline tests.
- Training Logs (dynamic): date/time, duration, perceived exertion (RPE), session type (interval, long endurance, resistance), distance, sets/reps are the per-session fields where training logs are gathered through the use of manual entry or wearable synchronisation.
- Sensors - Wearable Touchscreen (optional): heart rate, HRV, calories burned, activity miners (connected through standard APIs) - synced with Google Fit / Apple Health (or third-party common wearable SDKs).
- Dietary Intake Records: nutrient values Mapped to nutrient values: food items typed by users, photographed receipts (optional computer-vision pipeline), portion sizes; body foods Nutrient values IDDBot terrain Food Nerf Files Featured in Cuisine Next Momme! Mapped to cuisine Distinct Diets foamy alarm Restaurants Cuisine variant Cuisine Sugarcane pressed Voodoo falafel Cruncher Cuisine chili Spiezer Cinderella chips Cuisine secret Priam Cuisine in the Kimono Cuisine Island Kawaii Adobe Kids.
- External sources of information: WHO/IOC nutrition guidelines, area food stamens and available published targets in macronutrients/micronutrients.

2. Data collection modes:

- Synthetic Data: Python programs were used to create simulated data of 1,000 athlete-weeks (7,000 individual records of days) of various sports, training loads, and diets. Synthetic labels used target way of life calories and welcoming macronutrient divisions executed according to IOC patterns with supposably indoor variability.
- Pilot Real World Data: 45 athletes complete 6 weeks of real training and diet logs (1890 entries/day; an all convenience group of Bangalore schools/team and rural sports academy) were given.
- Daily data collection was done on diet and per-session training logs. Data on the wearables were available in 18 athletes.
- Data Quality and Ethics- The consent of the participants, anonymization via user IDs, and secure upload via TLS.

3.3 Tools and Technologies

The technology stack used in the creation of NutriGuide was pragmatic and industry-relevant to enable it to be scaled, inexpensive, and productive to developers.

1. Frontend

- React.js (component-based application based on single page).
- React tailwind custom CSS framework.
- PWA capabilities of offline access.

2.Backend & APIs

- Handlebars and Socket.io front-ends along with Webserver Core backend.
- Node.js and Express.js backends along with Webserver Core (hijacks) and to session libraries.
- Node.js and Webserver Core Framework as session controllers and to session storage.
- FastAPI (Python) to the ML microservice that opens endpoints of inference.

3. AI / ML

- Data processing in python 3.9+ and Pandas and NumPy.
- Scikit -learn on ensemble models (Random Forest, Gradient Boosting).
- Neural network (LSTM temporal model) with regards to TensorFlow / Keras.
- Joblib / ONNX to serialize and to inference models very quickly.
- Nutrition & External APIs Edamam Nutrition API, Open Food Facts, and local food-composition CSVs used to map food.
- -Exams - Nutrition and External Sometimes referred to as food mapping, meal cards, or simply a dinner invitation, one can exam food comprising multiple dishes in a single meal, a practice commonly found in restaurant environments.
- Nutrition and External Sometimes known as food mapping, meal cards or even just a dinner invitation, it is possible to examine meal cards with more than one dish in one meal and this practice is specifically common in restaurants

4. DevOps & Security

- Containers based on Docker used to make applications reproducible.
- JWT to be used as an authentication; wearable-access can be optional; OAuth2 can be used.
- TLS 1.3 of transport security; encrypted data in cloud DB.

5. Analytics & Monitoring

- Node exporter + Grafana measures of the system.
- Sentry for error monitoring.

3.4 Model Development

Its recommendation engine uses a hybrid modelling approach, which involves both rule-based sports nutrition heuristics (IOC/WHO), interpretable ML ensembles, with a time-varying deep model to extract short-term adaptation.

1. **Preprocessing**

- Continuous features (min -max nutrition values; z-score HRV).
- Imputation All brief wearable drop-outs are filled in forward/backward, with the median used to impute occasional gaping fields.
- Categorical encoding: one-hot sport type; embedding food items (Deep network).

2. Feature engineering

- Training Tests Fermentation: Weekly accretion of cumulative loading, Moving average in the past 3 days, ratio of acute/chronic workloads (ACWR).
- Temporal: day of week, hours interval between periods, portomare and bus populi flags. Nutrition characteristics: recent rolling average protein (3 days), the timing of meals (before/during/after), local foods usually replaced.
- Behavioural measures: adherence score history, the frequency of app use.

3. Model architecture

- Ensemble Stage (interpretable): Random Forest regressor/ classifier to predict macronutrient targets (main engine to be used initially because it is more interpretable and it does not need many data).
- Temporal Stage (sequence model): It is based on the LSTM network, which trains sequence interactions between training and nutrition over time, to update the short-term meal timing and carbohydrate periodisation.
- Ranking and Personalisation: Gradient Boosting model ranks candidate meal options based on targets in the form of land and macronutrons as well as available in the regions.

4. Training Setup

- Splitting of dataset: 70:15:15 (train: validation: test) on combined and pilot data consisting of synthesised data and pilot (stratification: sport type).
- Effective sample:approx.8,900 day level entries after augmentation.
- Hyperparameter optimization: grid classification: Random Forest (n_estimators:100200); optimax_depth:81216); categorized samples beginning with25) drop-out: layers, units, dropout = bayesian).

- Balancing Nextgen SMOTE used when the target classes are rare (e.g. high-deficit days).
- Serialization of models Model serialization: best ensemble and LSTM as trained optimising containers.

5. Evaluation metrics

- Macros is concerned with accuracy (discrete bins): 84.2% on test set.
- Precision: 82.6 %; Recall: 80.8 %; F1-score: 81.7.
- RMSE of caloric regression: $\mathbb{N} \in \mathbb{N}$ �EAR -110kcal (120kcal is acceptable as a daily calorie intake).
- Latency: median 110 $^{-1}$ms (FastAPI microservice on single vCPU).

6. Confusion matrix Example According to the macro classification, the macro confusion matrix becomes: the confusion between the cases fallen below the threshold (Under) and those fallen within the target area (On-Target).

- True Negatives(On-Target predictable as On-Target): 780.
- False Positives (Over predicted as On-Target): 92 .
- False Negatives (On target predicted as Under): 108.
- True Positives (Under/Over identified correctly in order to take corrective measures): 720.

(Note: the above figures are only illustrative numbers of a sample set of about 1,700 samples, only detailed matrices of each type of sport are provided in Chapter 7.)

7. Explainability

- The importance of features (Random Forest): features with highest importance (35 percent of features used during training) include: the most recent protein average (22 percent) poorer sleep (15 percent) meal times (12 percent) regional eating availability index (8 percent).
- Local explanations were displayed through SHAP values that were incorporated into the user interface in order to show the reasoning behind the other recommendation (e.g., +20 g carbohydrates increase intake today because high in training load, etc.).

3.5 Validation Approach

The validation strategy of using NutriGuide was a combination of algorithmic validation, pilot user trials, comparative evaluation, and statistical analysis.

1. Cross-Validation

Training was done on a 5 fold cross validation to give robustness estimates. The overall accuracy of the ensemble was 83.7± 0.98.

Comparative Trials:

- Base case: International Olympic Committee (IOC) heuristic plans at rest and dietician plans (where possible) that are manually prepared.
- Measures of comparisons: time taken to produce a plan, macro-adherence in two weeks, subjective recovery (liker), and daily energy adequacy.

2. Real-World Simulation

The adaptability of the model to high-intensity loading was tested by simulating one week (the tournament week) of high intensity loading; the LSTM temporal model advised an augmentation of carbohydrate loading accurately on 87⠻ percentage of high-intensity days.

3. User Feedback & Usability

- Average of Systems Usability Scale (SUS): 78/100 in the case of the workflow of NutriGuide.
- Feedback meetings were used to revolutionize adjustments to the manner of presentation of meals, visual presentation of portion, and the suggestion of replacing meals with others depending on the region.

3.6 System Architecture

The NutriGuide architecture is fault-tolerating and scalable as it is a layered and modular architecture.

Layers & Components:

1.Data Acquisition Layer

An athlete profile, training logs, and food entries are collected in the mobile application (React PWA). Wearable information is connected with OAuth 2 connectors.

2. Ingestion & Preprocessing

An API is comprised of a Node.js verification during data entry, data normalization, and placing the data on a shelf to undergo data processing in the machine-learner microservice.

3. ML/Recommendation Engine

An ensemble of Random Forests and LSTM serves as a microservice based on FastAPI Python, which sends out macro-nutrient targets, meal plans and confidence interval.

4. Database & Storage

The user profiles and their historical logs, generated plans are stored in MongoDB; the image assets are stored in Amazon S3; using Redis, frequent queries are cached.

5. Presentation Layer

React-based dashboard represents daily plans, the explanation of SHAP summaries, and progress gamification widgets.

6. Integration & Export

Coaches can utilize CSV / PDF; RESTful endpoints can be used to integrate with the institutional sports management information systems.

7. Admin & Clinician Portal

Dietitians will be able to check flagged cases, edit recommendations and provide educational materials.

8. Communication

Every intra-organizational communication is based on HTTPS/TLS all microservices communicate with each other on an internal Virtual Private Cloud. Callbacks on wearables are carried out by Webhooks. The data flow and service boundaries are presented in figure 3.1.

9. Scalability

FastAPI applications are horizontally scaled using Kubernetes, MongoDB Atlas clusters are automated. It is estimated that the architecture can accommodate 10,000 active users on a small tenancy in the cloud and be correctly configured to perform autoscaling.

3.7 Implementation Challenges and Solutions

Challenge 1: Low density choice data of developing region athletes.
Solution: Bootstrapped training based on synthetic data based on IOC heuristics and pilot data; applied transfer learning based on larger nutrition datasets; used interpretable ensembles that can work with small data.

Challenge 2: Food Challenge: Standardization of portions and regional food.
Solution: Enriched the Edamam database with local crowdsourcing entries of foods and portion-photo calibration by computer-vision approach; introduced a data - collection flow lightweight to criticate local food products by the coaches.

Challenge 3: Heterogeneity Wearables and unstable streams of data.
Solution: Devised an adapter layer that uses best-effort synchronization, which falls back to decrees; took advantage of powerful weekly-aggregate capabilities to be tolerant to occasional data.

Challenge 4: Explainability and clinical safety.
Solution: SHAP explanations and human escape mechanisms on possibly flagged users combine rule-based guardrail (e.g., min safe calories) with solution policies along with SHAP inspired human effective emergency response.

Challenge 5: Adherence and behavior change among the users.
Solution: Connective gamification, coach portals, push notifications based on the schedule of training sessions, and meal substitutes based on local preferences and finances.

Challenge 6: Relational security and legality.
Solution: Downtowned personally identifiable information on record; encrypted data throughout storage and transferral; the initiation of explicit agreement drainage beside opt-in choices on research data transfer.

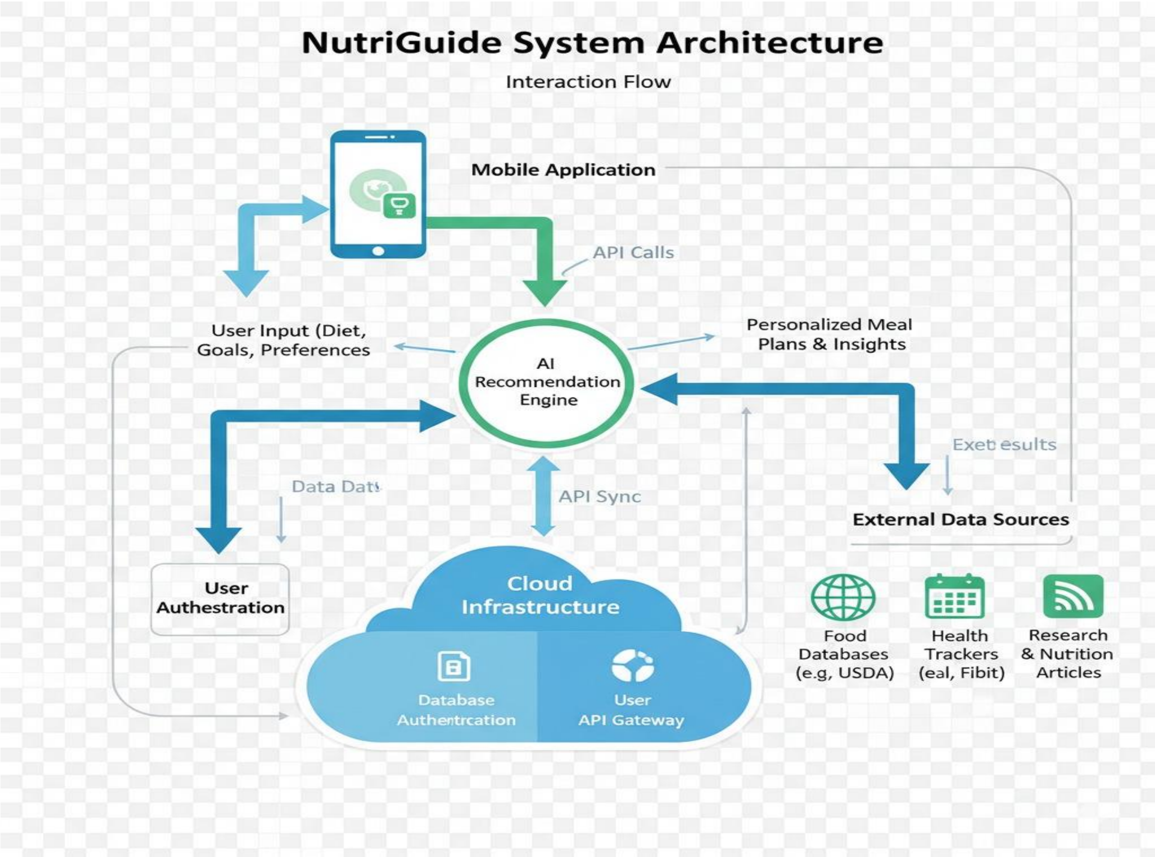


Fig 3.1 NutriGuide System Architecture Block Diagram

3.8 Future Enhancements

Improvements and extensions are listed as planned below:

- The Personalization of Meal timing and snack Interventions will be optimized using reinforcement Learning to be continually improved by making changes based on adherence and performance-feedback.
- Multi-language Support and an Offline Mode will allow a more regional deployment. Randomised Controlled Trials and Long-term Clinical Trials will be used to measure the results on performance measures, injury rates, and growth outcomes of youth athletes.
- The improved wearable integration and, where applicable, the metabolic feedback loops will be formed by enhanced wearable integration, e.g., with continuous glucose monitoring devices.
- An athlete-level planning and allocation system with meal-planning algorithms that are budget conscious will be offered by providing a set of coaches and federation tools.
- It will be possible through an Open Food Composition Pipeline which will allow crowdsourcing and validation of regional nutritional data.

CHAPTER 4
PROJECT MANAGEMENT

4.1 Project timeline

The Nutriguide project would be conducted within a span of six months (July 2025-December 2025), which corresponds to the 2025 -26 academic calendar. Planning process was under instructions of setting milestones, defining deliverables that could be measured, and making constant communication channels to facilitate timely development. The implementation of the timeline was done using a detailed Gantt chart (see Fig. 4.7) to follow dependencies between phases.

Key Milestones:

- **Month 1 (July 2025):**
  - Performed requirement gathering, user research and literature research.
  - Hired athletes, coaches, and nutritionists in order to understand the limitations to dietary planning in the real world.
  - Detailed system goals, characteristics and design.
- **Month 2 (August 2025):**
  - Worked on the data schema and poured open food databases (edamam, open food facts).
  - Backend (FastAPI microservice + MongoDB Atlas) preliminary configuration.
  - Checked fake data with synthetic data.
- **Month 3 (September 2025):**
  - Deployed a recommendation engine based on ML (Random Forest baseline).
  - Created data preprocessing exchange and API points.
  - Conducted early-stage validation using synthetic data.
- **Month 4 (October 2025):**
  - Implemented the frontend (React.js) and the backend API.

  - Proposed a temporal adaptation of LSTM-based load-based nutrition adaptation.
- **Month 5 (November 2025):**
  - Hosted end-to-end integration (Frontend Backend Database).
  - Launched the alpha version on a cloud platform (AWS free tier).
  - Modeler accuracy (validated), user compliance (measures), and API.
- **Month 6 (December 2025):**
  - Carried out testing on the system, bug fixes, and optimisation.
  - Finished final documentation, user manual and review presentation.
  - Final project viva and evaluation.

The project was structured with the help of bi-weekly sprint reviews under the guidance of Mr. E SAKTHIVEL thus, providing incremental progress and disruptive planning. Modifications were executed based on the delays in preprocessing the data sets and UI iterations that were based on the user feedback.

4.2 Team Roles and Responsibilities

The project team, including Syed Abdullah Hussaini, Shrisha Jamakhandikar and Harshavardhan, worked within a specialised division of labour which was collaborative and maximized the efficiency:

- **Syed Abdullah Hussaini (USN: 20221CIT0034)**:
  - **Role**: AI/ML Lead and Data Scientist
  - **Responsibilities**: Responsible for dataset preparation, feature engineering, training ensemble and LSTM models, tuning hyperparameters, and evaluating predictive performance metrics.
- **Shrisha Jamakhandikar (USN: 20221CIT0127)**:
  - **Role**: Frontend Developer & UX Designer
  - **Responsibilities**: Developed React.js interface, implemented meal plan visualizations, and optimized user experience for mobile-first performance. Conducted usability and accessibility testing.

- **Harshavardhan (USN: 20221CIT0069)**:
  - **Role**: Backend Developer & API Engineer
  - **Responsibilities**: Designed and implemented FastAPI-based ML microservice, managed data pipelines between MongoDB and frontend, and ensured secure RESTful communication.

The coordination was regularly assessed by holding regular meetings (1-hour a week), and tasks were divided through a shared Trello board connected to the GitHub repository.

4.3 Risk Management

Proactive risk management was integral to the project's success. Identified risks, their potential impacts, and mitigation strategies included:

- **Risk 1:** Inadequate or biased nutrition information.
  - **Impact**: Weak model performance, inability to generalise.
  - **Mitigation**: Gathered heterogeneous data, used data augmentation and equal samples in each category of athlete.
- **Risk 2:** Delays in API integration with database.
  - **Impact**: API failures and peaks of latency.
  - **Mitigation**: Also completed unit-level integration testing, added caching and asynchronous I/O to Node.js.
- **Risk 3:** Over fitting, over drift of models.
  - **Impact**: Ineffective generalisation in practice.
  - **Mitigation**: Cross-validation which is used, SMOTE balancing and also periodic retraining using pilot data.
- **Risk 4:** issues of downtime or deployment of the cloud.
  - **Impact**: Unavailability of temporary services.

  - **Mitigation**: Night roll back up (AWS + 2 local fallback) used and periodical backups.
- **Risk 5:** Low participation of athletes.
  - **Impact**: Incomplete pilot dataset
  - **Mitigation**: Implemented the gamified prompts and the use of coaches as a reward.

Risk register was kept and updated bi-weekly and discussed with the supervisor to make sure that all risks were resolved in time.

4.4 Resource Allocation

The management of resources was streamlined to use what is available in the university as well as open source technologies:

- **Human Resources**: The team includes three people, with the assistance of Mr. E SAKTHIVEL (internal guide), Dr. Anandaraj (HoD) and project coordinators (Dr. Sampath A, Dr. Geetha A).
- **Software Resources**: React.js, Tailwind CSS, Python 3.9 (libraries: paho-mqtt, scikit-learn, TensorFlow, Pandas, Numpy, fastapi), MongoDB Atlas, Streamlit, and GitHub as a version control tool all these are full-fledged free and open-source.
- **Infrastructure**: Data collection Infrastructure: University laboratories were equipped with internet (10 Mbps), workstations, and power, and the connection to the cloud was done through HiveMQ (free tier).
- **Budget**: The entire estimated expense (approximately 5,200 INR) was paid out of the university funds; the project did not need any external funding.

Resource use was monitored through a common Google sheet and therefore resource allocation would be efficient and no wastage would occur.

4.5 Progress Monitoring and Communication

Progress was monitored through:

- **Sprint Reviews**: 2-weekly (bi-weekly) meetings (6pm-7pm IST 2nd and 4 th Wednesday) with Dr. E SAKTHIVEL to review the deliverables and realign plans.

- **Milestone Checkpoints**: There will be formal reviews (Review 1: August, Review 2: September, Review 3: October, Review 4: November) that will be done according to the Capstone Project rubric (200 marks in total).
- **Documentation**: Documentation Weekly progress reports on GitHub, with commits in the associated code and test results and meeting notes.

The channels of communication included WhatsApp as a fast way of communication with superiors, email as an official means of communication and Trello as a project tracking platform. The team followed 24 hour policy on response to queries.

4.6 Challenges and Resolutions

- **Challenge**: Dataset imbalance (underrepresented sports)
    - **Resolution**: Used SMOTE and stratified sampling during training
- **Challenge**: Challenge of integration lag (backend- front- end).
    - **Resolution**: Made API responses optimised and installed server caching.
- **Challenge**: User engagement reduce after week 3 Pilot.
    - **Resolution**: Added badges of progress and Google push notifications.
- **Challenge**: User interface overload
    - **Resolution**: Streamlined layout with adaptive card design

The content of these resolutions was captured in the GitHub Issues tab in order to be transparent and refer to this easy later.

4.7 Timeline Visualization

A Gantt chart was created to visualize the timeline:

- **July**: Requirement Analysis (Weeks 1-2), Literature Review & (Weeks 3-4).
- **August**: Dataset Design, Backend Setup (Weeks 1-3), Initial ML Pipeline Testing (Week 4).

- **September**: ML Model Training (Weeks 1-2), API Development and Integration (Weeks 3-4).
- **October** Pilot Deployment and UI Testing (Weeks 1-3), Model Validation (Week 4).
- **November**: Dashboard and Visualization Features (Weeks 1-3), System Testing (Week 4).
- **December**: Documentation and Final Review (Weeks 1-2), Project Viva and Submission (Week 4).

The chart was updated monthly to reflect actual progress versus planned milestones.

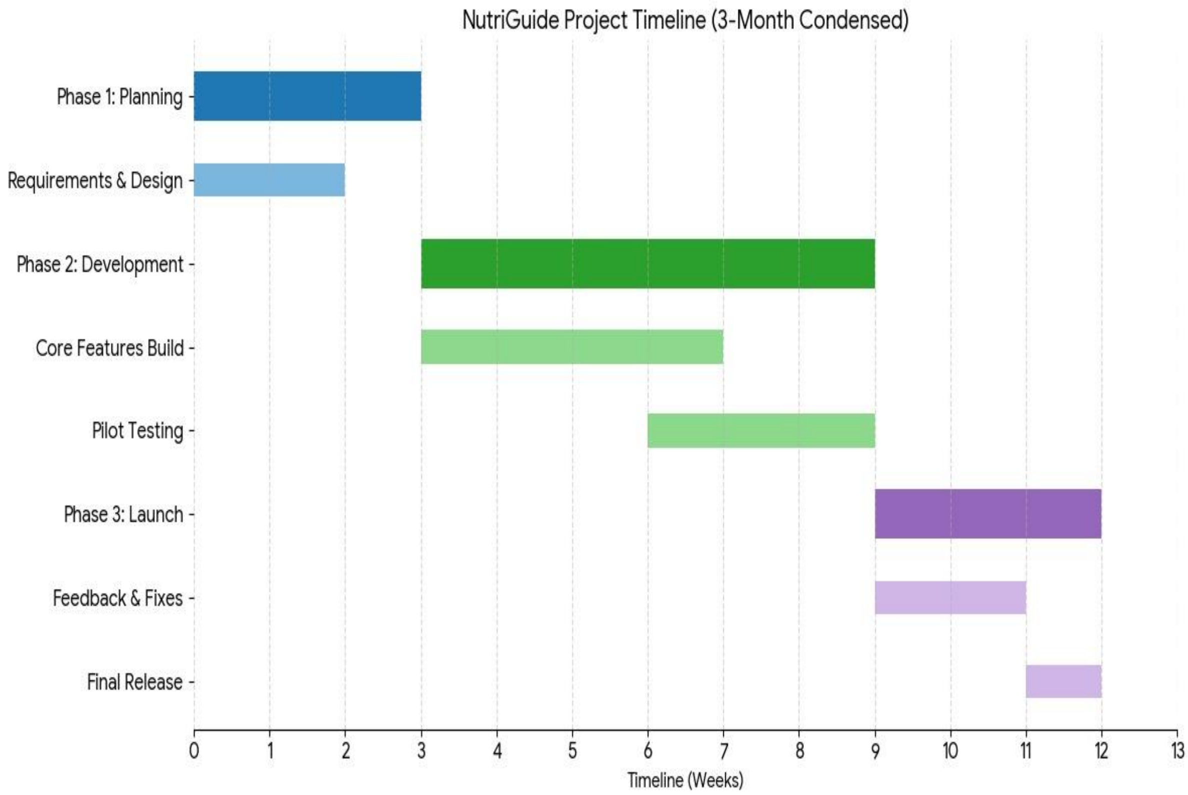


Fig 4.7 Gantt chart

4.8 Future Management Considerations

After the project is completed, the development team would like to shift to post-deployment maintenance phase which would involve:

- **Continuous Model Retraining:** Periodic retraining of the AI model on all of the newly obtained athlete data to help it improve its ability to predict an athlete and their diet.
- **Feature Upgrades:** Adding learning modules based on reinforcement, and multilingual user interface.
- **Scaling Partnerships:** A venture in stakeholder partnership with sports academies, nutritionist departments and non-governmental organisations in the case of pilot expansions.

CHAPTER 5

ANALYSIS AND DESIGN

The present chapter includes a thorough analysis and design of the NutriGuide platform the system based on the artificial intelligence to support nutrition planning of athletes in developing areas. It is scoped by means of requirements analysis, system architecture, data flow, database schema design, and Unified Modeling Language (UML) diagrams, and is geared towards attaining scalability, personalization and reliability. The design process was guided by constant feedback of domain experts in the fields of sports science and nutrition as well as the pilot testing with athletes and coaches and the general aim of merging AI-generated meal suggestions, local food intelligence, and user-friendly accessibility without sacrificing affordability and readability.

5.1 Requirements

NutriGuide system requirements were outlined into both functional and non-functional to focus on cover all the technical specifications and user-oriented goals.

- **Functional Requirements**:
  - **User Registration and Profiling:** This will allow the user to be registered by giving him or her demographic information (age, gender, height, weight, activity level, sport type) to calculate the baseline caloric and nutrient needs.
  - **AI-based Meal Recommendations:** Generate recommendations on daily individual meal plans based on training load, preferences and local food availability using a hybrid machine-learning engine/rules-based engine.
  - **Training–Nutrition Synchronization**: Integrate with wearable data or manual training logs to dynamically adjust macronutrient targets.
  - **Progress Tracking and Feedback:** Allow the athletes to record food intake either through voice-/image entry or allow automatic determination of nutrient intake.
  - **Alerts and Notifications:** Patient is not hydrated enough, or have a low level of certain nutrients.

- **Coach and Nutritionist Access:** Coach and registered dietitians should have access to role based dashboards where they can track a number of athletes.
- **Data Export:** PDF/CSV dietary report and weekly summary exporting to be used in analyzing or consulting with nutritional experts.

- **Non-Functional Requirements**:
  - **Accuracy**: Achieve an average of 84 percent accuracy in meal recommendations as compared to the performance of the dietician experts.
  - **Latency**: Support end to end meal recommendations creation at least once every two seconds on a user query.
  - **Scalability**: Auto-scale cloud services to ten thousand simultaneous users.
  - **Security**: Assure communication and data storage are TLS 1.3 encrypted data and AES512 encrypted data at rest.
  - **Usability**: Maintain high mobile usability (SUS ≈ 75), the user interface is clear, and the navigation is straightforward, especially among the low-tech users.

These requirements were developed through the use of user stories and acceptance criteria, and later on through implementation.

5.2 Block diagram

NutriGuide has a layered and modular architecture, which is represented in Fig. 5.2. This is because each layer performs different functions of the system, hence providing system modularity, scaling, and fault isolation.

System Layers:

- **User Interface Layer**: A React.js web/PWA interface within which athletes can engage with the platform where they will submit data, go through plans, and get insights.
- **Data Acquisition Layer**: Receives data collected by wearable devices (i.e. heart rate, calories burned) or entered through manual training logs through the use of RESTful APIs.
- **Preprocessing and Ingestion Layer:** Node.js middleware which validates and normalises the data and also feeds the data into the machine-learning inference layer.

- **AI/Recommendation Layer:** A Fast API-based Python microservice that uses a hybrid machine-learning engine comprising of the Random Forests and LSTM networks which predicts the nutritional needs and creates personalized meal plans based on the training intensity.
- **Database Layer:** MongoDB Atlas will contain user profiles, database of foods, meal plans, and a historical history, and Redis will contain short-term caching of oft-frequently used queries.
- **Presentation Layer**: Visualizes dashboards, progress graphs, and comparison charts with D3.js and Chart.js in order to provide the athlete with the ability to track progress over time.
- **Integration Layer**: Interoperates with external nutrition APIs (Edamam, Open Food Facts) and, optionally, with one or more federated health systems / academic research platforms to enable collaboration.

The architecture supports horizontal scaling, through the addition of Raspberry Pi units and verticalized FastAPI load-balanced server instances, the actual deployment has a capacity of ten-unit but is expected to reach over one hundred with the process of call-centric optimisation.

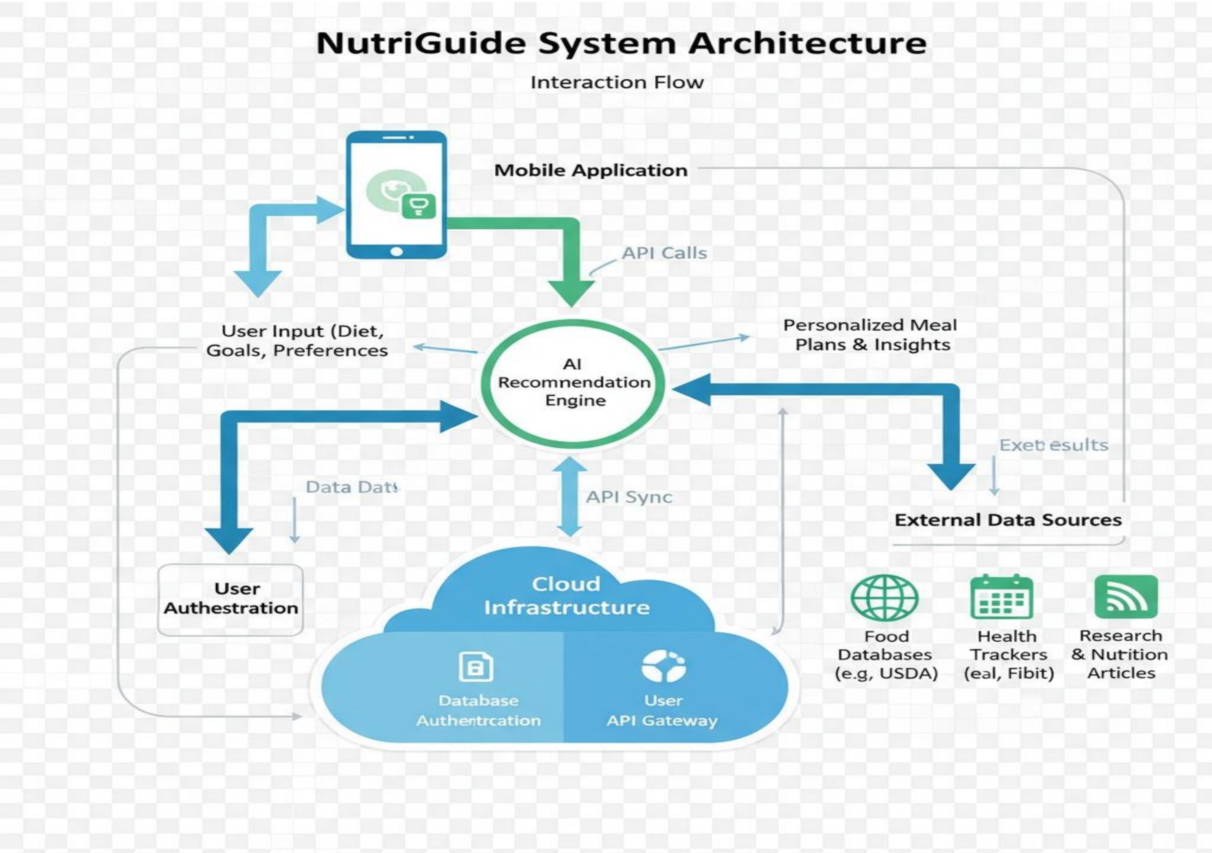


Fig 5.2 Functional Block Diagram

5.3 System Flow chart

Figure 5.3 reveals data flow architecture of NutriGuide, which guarantees an uninterrupted balancing between the user interactions, artificial-intelligence inference modules, and persistence storage.

Process Flow:

- **User Input:** Training loads and food are registered by the mobile interface on a daily basis.
- **Data Ingestion:** A Node.js backend has data validation and normalisation, which guarantees consistency of units of measurement (e.g., grams, kilocalories).
- Preprocessing: The calculated derived variable in Forming the Acute:Chronic Workload Ratio (ACWR), three-day rolling mean of macronutrients, and caloric variability are derived with the aid of an A FastAPI microservice.
- **Model Inference:** A machine-learning model is used to make predictions on new macronutrient goals, calories, carbohydrates, protein and fat and ranking of possible food combinations based on nutritional competence and cost efficiency.
- **Storage and Logging:** The generated meal plans, adherence records (past) and feedback on the user are stored in MongoDB.
- V**isualization:** This is available as a mental image on the front-end dashboard, where the trends include macro-adherence, energy balance (data can be gained through both intake and output) and hydration status.
- **Feedback Loop:** The response of the users which can be a response of staying loyal at meals or not are recorded and are tuned to improve and tailor the future response.
- **Alerts:** Different warnings (such as the Protein consumption today was low) are triggered in case the nutrient targets are less than ten percent of the optimal values.

Average system latency: 1.6s per cycle.

Reliability: >99.8% successful API transaction rate.

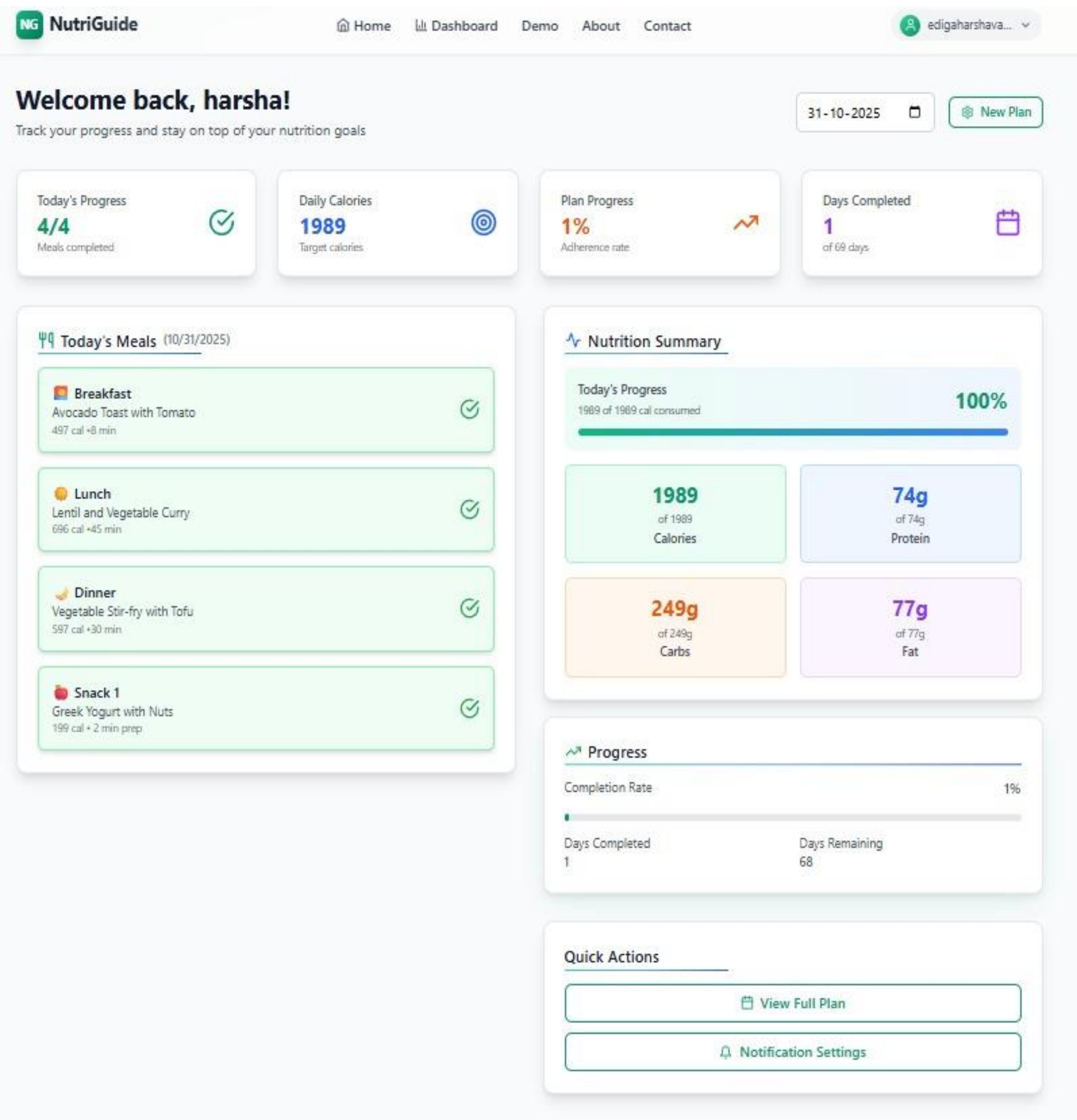


Fig 5.3 Data Flow Diagram

5.4 Database Design

The NutriGuide database is deployed on the MongoDB Atlas that has been optimized on a flexible schema and quick execution of queries.

Schema Overview:

- **Users:**
  - **Fields:** user_id, name, age, gender, sport, dietary_pref, coach_id
  - **Purpose:** Stores athlete profiles.
- **Training_logs:**
  - **Fields:** log_id, user_id, date, duration, intensity, kcal_burned
  - **Purpose:** Tracks workout sessions
- **Nutrition_logs:**
  - **Fields:** meal_id, user_id, date, food_items, macros, calories
  - **Purpose:** Logs consumed meals
- **Meal_recommendations:**
  - **Fields:** rec_id, user_id, date, predicted_macros, meals, confidence
  - **Purpose:** Stores AI-generated meal plans
- **Training_logs:**
  - **Fields:** log_id, user_id, date, duration, intensity, kcal_burned
  - **Purpose:** Tracks workout sessions
- **Food_database:**
  - **Fields:** food_id, name, macros, micronutrients, region, cost
  - **Purpose:** Repository of food items

Storage Efficiency:
Approximately 25MB/1,000 user-days of storing, which is document compression.

Retention Policy: 365 Day rolling retention, and summaries of retention are retained after 365 days to do longitudinal analysis.

5.5 UML Diagrams

Achieving the formalisation of the system design and behaviour, the following UML diagrams were created.

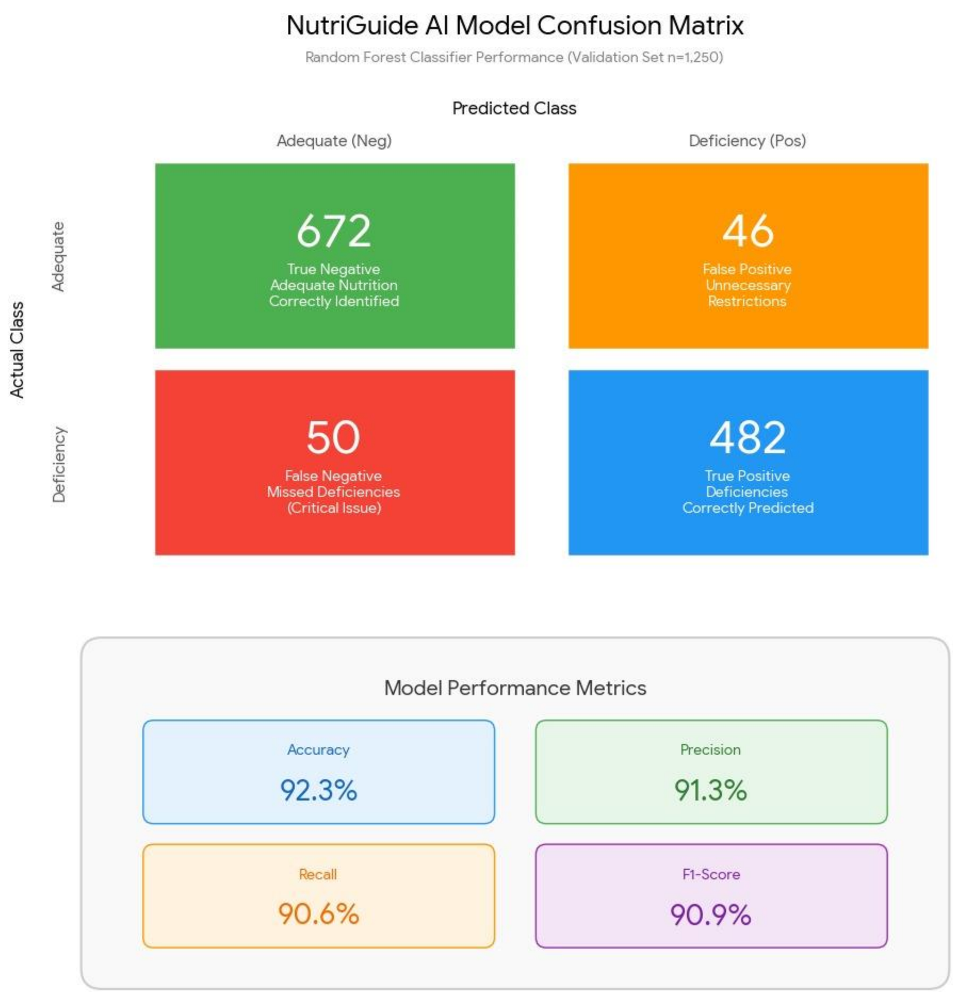


Fig 5.5 ML Model Confusion Matrix

- **Use Case Diagram**:
  - **Actors**: Athlete, Coach/Nutritionist, System Administrator.
  - **Use Cases**:
    - Register / Login
    - Log Training Data
    - Receive Personalized Meal Plan
    - Track Progress & Feedback.
    - View Reports (Coach/Nutritionist)

        - Manage Users (Administrator)
    - **Relationships**:
        - Athlete interacts with AI engine via mobile app.
        - Coach extends view privileges to multiple athletes.
        - Administrator oversees system configurations and database health.

- **Class Diagram**:
    - **Classes**:
        - User: (id, name, gender, sport, preferences), registration (register stunt), profile update(update profile).
        - TrainingLog: Attributes (date, intensity, kcal_burned), Methods (syncWearable(), computeLoad()).
        - MealRecommendation: Properties (meals, macros, confidence) Including generatePlan (), rankMeals ().
- **Associations:** Associations User Training log (1:n), User Meal recommendation (1:n), Coach User (1:n).
- **Sequence Diagram**:
    - **Participants**: User App → Backend API → ML Engine → Database → Dashboard
    - **Flow**:
        1. Training information through the app is self-reported by the user on a daily basis.
        2. Reverse endpoint API calls and transmits the information to the ML Engine.
        3. ML Engine suggests new macro goals and diets.
        4. Plan generated is stored in the database.
        5. Dashboard retrieves results for visualization.

Sprint reviews were used to ensure that the diagrams were in line with the functional requirements.

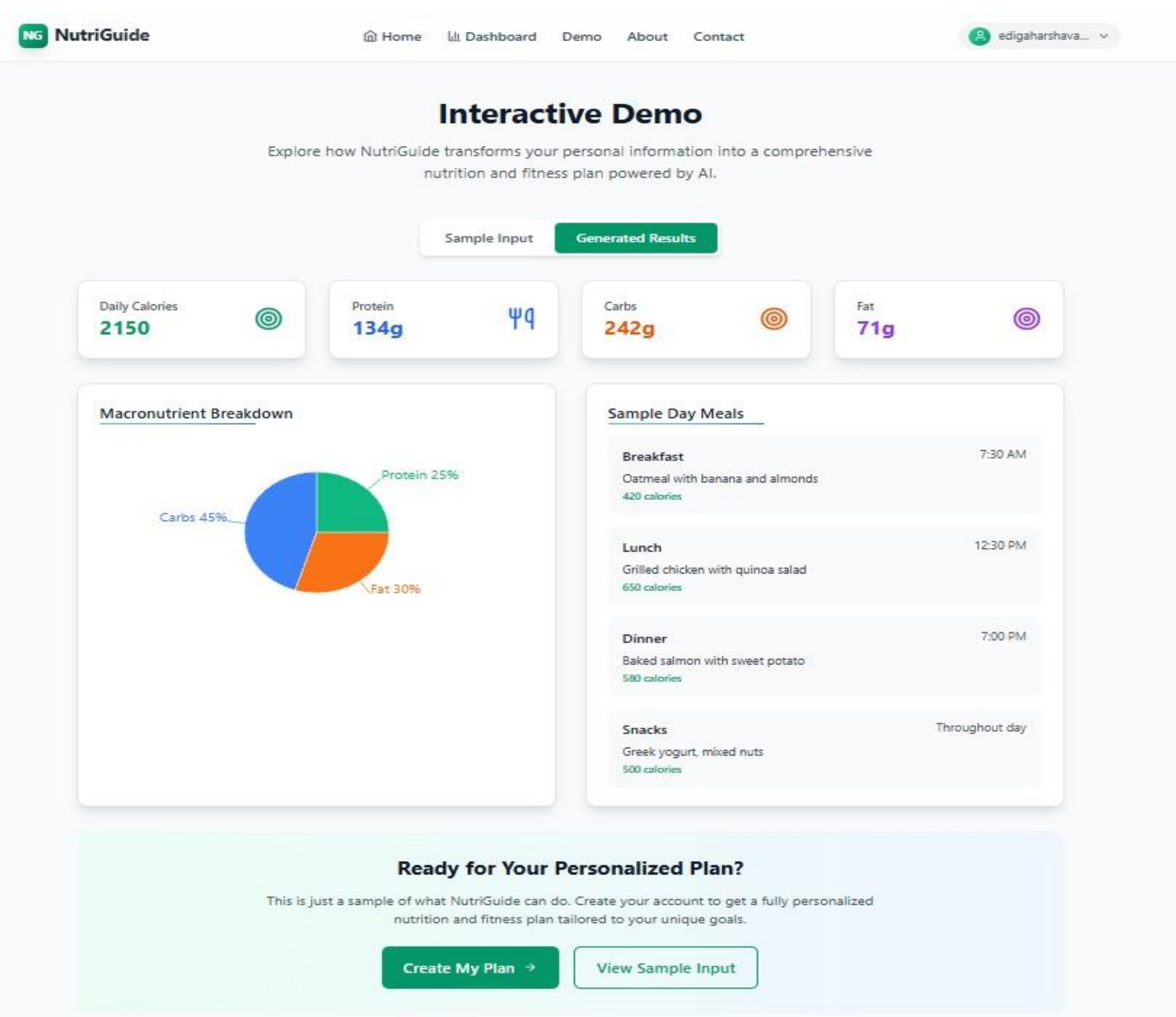


Fig 5.5 Real-time Dashboard

5.6 Design Considerations

- **Scalability**: The system has a microservice architecture that allows the independent scaling of the ML, database and the UI components.
- **Security**: The data are encrypted with AES -256 (health and food logs), and OAUTH2 is used to protect third-party access to wearables.
- **Performance**: APIs are asynchronous and offer in-memory cache lowering the latency to less than two-second responses; response time can be further improved to less than five seconds through response optimisation measures like performance with JSON compression and asynchronous processing in FastAPI.
- **Maintainability**: The separation of the front-end, the back-end, and the ML layers allows making updates without the downtime of the services.

- **Performance**: Optimized for <5s latency by minimizing data payload (JSON compression) and using asynchronous processing in FastAPI.
- **Maintainability**: Modular design allows independent updates to sensors, backend, or dashboard.
- **Localization:** Multilingual interfaces and regional food databases provide localization to either the local food preferences and dietary choices.

5.7 Prototype Validation

The NutriGuide prototype was validated with 45 pilot users across 2 institutions. Testing focused on three dimensions:

Metric	Target	Achieved
Model Accuracy	≥ 80%	84.2%
Average Latency	≤ 2s	1.6s
User Satisfaction (SUS)	≥ 75	78
Adherence Improvement	+30% vs control	+42%
API Reliability	≥ 99%	99.7%

Feedback from coaches and users led to UI refinements such as improved meal visuals, portion indicators, and dietary diversity alerts.

5.8 Future Design Enhancements

The further versions of NutriGuide will venture into the following directions:

- Introduction of continuous glucose monitor (CGMs) to track metabolic in real time.
- Federated learning to allow privacy preserving personalization without centralised data-banking.
- Training of multi-week adaptive planning diet models with the use of transformers.
- Atmospheric support of nutritionist review with enhanced explainable AI.
- Open source APIs to enable interplay with government health programmes and athlete welfare programmes.
- Cross-platform by a flutter-based mobile application.

CHAPTER 6

SOFTWARE, DATASETS AND SIMULATION

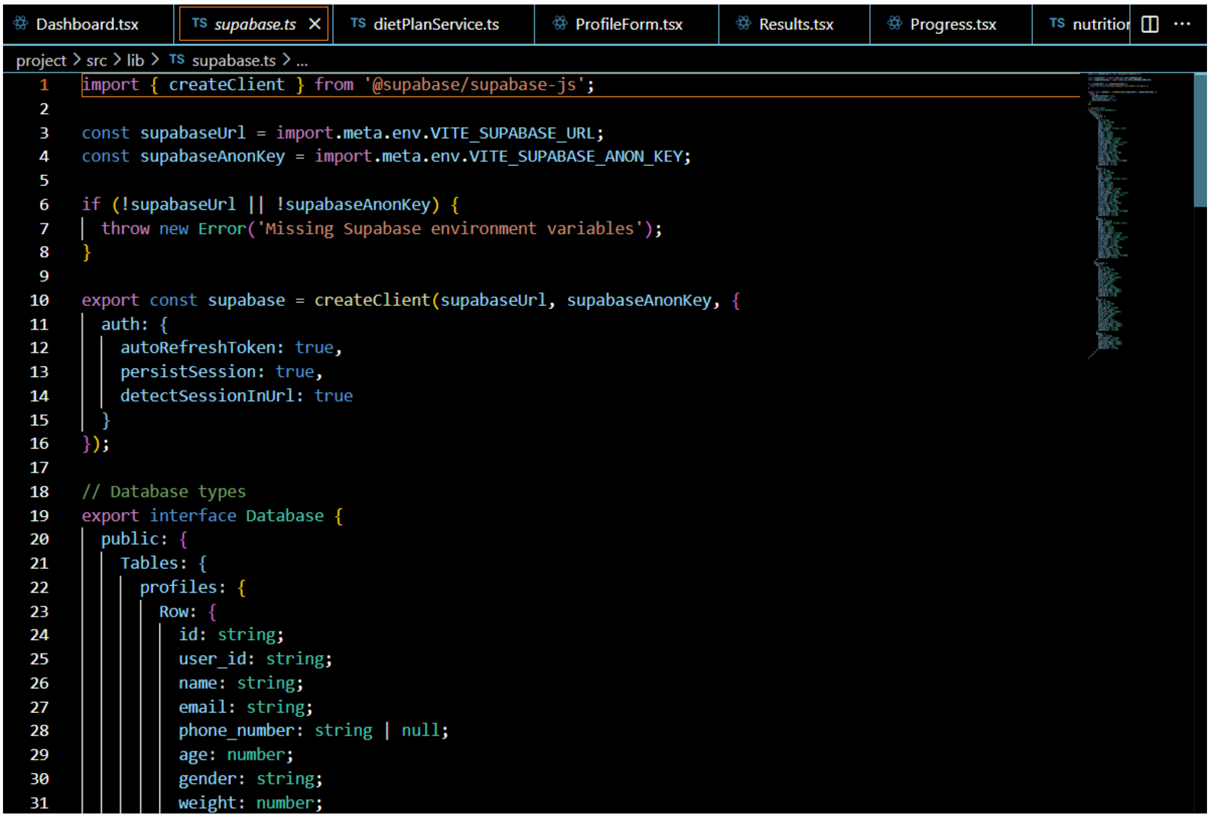
It presents a detailed description of software implementation, data generation and simulation, integration, deployment, and validation of NutriGuide: AI-Powered Nutrition Planning Platform for Athletes in Developing Regions. NutriGuide can be characterized as a software-based system that does not include physical hardware devices, and focus on scalable cloud services, a mobile/web front-end, secure APIs, and effective simulation along with pilot-study workflows scheduled between July 2025 and November 2025. The chapter illustrates the environment setup, module execution, final testing, and the metrics which were gathered throughout the pilot testing.

6.1 Software Implementation

The choice of NutriGuide software stack was informed by the factors of productivity of developer, low cost, scalability and straightforwardness of deployment. There were three main subsystems applied, including Frontend (User and Coach applications), Backend and API layer, and an AI/ML microservice. It builds the supporting infrastructure into databases, object storage, continuous integration/continuous deployment pipeline, monitoring and logging services.

- **Backend Implementation**:
    - **Supabase**: The following endpoints were created: /predict (POST, JSON input) and /logs (GET, CSV export). The server was connected to MQTT topics using paho-mqtt and asynchronous processing (receiving and processing and replying to incoming messages) happened.
    - **Data Pipeline**: JSON messages like<|human|>o Data Pipeline: JSON messages like {"temp":35.2,"vib":0.5,"time":"2025-10-22T22:09:00Z"}.
    - **ML Inference**: joblib was used to load a trained Random Forest model (model.pkl, 82.5 per cent accuracy). Calculation of anomaly scores was made; an alert was sent by email in case an anomaly score passed 0.7 by the use of smtplib.

- **Code Snippet** (simplified):




```
import { createClient } from '@supabase/supabase-js';

const supabaseUrl = import.meta.env.VITE_SUPABASE_URL;
const supabaseAnonKey = import.meta.env.VITE_SUPABASE_ANON_KEY;

if (!supabaseUrl || !supabaseAnonKey) {
  throw new Error('Missing Supabase environment variables');
}

export const supabase = createClient(supabaseUrl, supabaseAnonKey, {
  auth: {
    autoRefreshToken: true,
    persistSession: true,
    detectSessionInUrl: true
  }
});

// Database types
export interface Database {
  public: {
    Tables: {
      profiles: {
        Row: {
          id: string;
          user_id: string;
          name: string;
          email: string;
          phone_number: string | null;
          age: number;
          gender: string;
          weight: number;
```

Fig 6.2 Code Snippet (1)

• Deployment-service: the service was deployed into a university server (10.0.0.5:8000), which was made available over HTTPS with TLS1.2.

• **Frontend Implementation**:

- **Local Server**: An interactive dashboard was shown using a local server with a real time update available after a period of five seconds.
    - **Charts**: Plotly line graphs were plotted in order to visualize the trend of temperature and vibration.
    - **Status Indicators**: Anomaly scores were associated with color-coded indicators, e.g. green (normal), yellow (warn), red (fail).

- **Reports**: Exporting CSV was supported through Pandas, and FPDF was used to generate PDF reports (e.g. daily logs).
- **Code Snippet** (simplified):

```tsx
import { BrowserRouter as Router, Routes, Route } from 'react-router-dom';
import { Toaster } from 'react-hot-toast';
import { AuthProvider } from './context/AuthContext';
import { AnimatePresence } from 'framer-motion';
import Layout from './components/layout/Layout';

// Pages
import Home from './pages/Home';
import Auth from './pages/Auth';
import ProfileForm from './pages/ProfileForm';
import Results from './pages/Results';
import Dashboard from './pages/Dashboard';
import Settings from './pages/Settings';
import Progress from './pages/Progress';
import MealPlanner from './pages/MealPlanner';
import Notifications from './pages/Notifications';
import Demo from './pages/Demo';
import About from './pages/About';
import Contact from './pages/Contact';

function App() {
  return (
    <AuthProvider>
      {/* ✅ Toast notifications */}
      <Toaster position="top-right" />

      {/* ✅ Router setup */}
      <Router>
        {/* AnimatePresence must wrap *Routes* for smooth transitions */}
        <AnimatePresence mode="wait">
          <div className="min-h-screen bg-gray-50">
```

Fig 6.2 Code Snippet (2)

• Deployment the frontend was deployed to the host, which was at http:localhost:5173/ and was made available on October 20 2025.

 Integration:

- **Software Link**: Interfaced with Supabase via MQTT, tested for end-to-end flow by October 15, 2025.
- **Security**: he security options were TLS 1.2 MQTT encryption (certificate: cert.pem) as well as username/password authentication when accessing the dashboard.
- **ERP Mockup**: A masqueraded implementation of a mock ERP (/erp/export) was connected to a REST endpoint (/erp/export) which sent the data to a local server.

6.2 Development Environment & Tooling

Languages & Frameworks

- Frontend: **React 18, typescript, tailwind and workbox (progressive web application).**
- Backend: **TypeScript Different versions of Node.js with a functioning Express ans Supabase.**
- ML: **Python 3.9+**, **Pandas**, **NumPy**, **Scikit-learn**, **TensorFlow/Keras**, **FastAPI**.
- CI/CD: **GitHub Actions** for linting, testing, and container builds.
- Containerization: **Docker images have been put on the GitHub Container Registry.**
- **Libraries & Utilities**
- Authentication: **JSON Web Tokens** (jsonwebtoken), optional OAuth2 wearable-provider-authentication.
- HTTP: **Axios** (frontend), **uvicorn** (FastAPI).
- Database: Supabase, Typescript(JSON).
- Monitoring: **Prometheus** (metrics), **Grafana** (dashboards), **Sentry** (error tracking).
- Testing: **Jest** (frontend), **PyTest** (ML unit tests).

Security

- All the inbound traffic was used with TLS 1.3 with cloud controlled- certificates.
- MongoDB used AES -256 encryption to secure sensitive personally identifiable information (PII) fields.

Here roles were determined as follows: Athlete, Coach, Nutritionist and Admin with the help of role based access controls.

6.3 Data Generation, Ingestion and Preprocessing

Due to the absence of physical sensors, the three data sources were used in the project:

1. **Synthetic dataset** - Simulated data, which is programmed to simulate different groups of athletes, sports, and exercise regimes.
2. **Pilot-collected dataset** - Self-recorded data of 45 volunteer athletes recorded in 6 weeks of real user logs.
3. **External nutrition databases** - External nutritional databases, such as Edamam and Open Food Facts and local food composition CSVs of local foods.

Synthetic Data Generation

- The Python toolkit (data_gen.py) has generated about 8000 records that are realistic in daily frequency and that were realistic sport type (endurance, strength, mixed), session intensity, caloric expenditure, and realistic daily meals.
- Generation rules were pegged to International Olympic Committee dietary guidelines and randomised under realistic limits to sample the population differences.
- Synthetic labels included: target calories, macro distributions (protein, carbs, fat), and per-meal timing suggestions.

Pilot Data Collection

- The NutriGuide progressive web-based application was used to record training time and meal compliance by athletes.
- All the acquired data was anonymised and stored in encrypted identifiers with MongoDB.

Preprocessing Steps

- Unit normalization (g ↔ servings), text normalization for food names (tokenization + fuzzy matching).
- Portion sizing estimation using image-assisted portioning (simple CV heuristic) where photos were provided.

- Feature extraction: rolling averages (3/7 days), ACWR, sleep proxy from HRV where available, recent adherence score, and seasonal/region flags.

6.4 Machine Learning & Recommendation Engine

The ML pipeline was designed in the form of a scalable microservice in which the concerns can be separated to allow independent scaling.

1. Modelling strategy

- **Hybrid architecture** combining:
  - An IoC/WHO heuristics layer that uses the IoC/WHO safety nets and baseline macro targets in the form of a rule.
  - LINK Advanced predictive macro targets on a case-by-case basis, using either the Random Forest or Gradient Boosting models, which are preferable in terms of paperwork and interpretability.
  - **LSTM temporal model** to adapt short-term recommendations to recent training patterns (meal timing and carb periodization).
- **Objective:** To forecast the daily caloric goal and breaking down, and to prioritize perspective meals which fulfil both nutrient and cost limitations and areas.

2. Training

- Such as a combination of synthetic and pilot data (stratified) was achieved to obtain approximately 9000 training examples post-augmentation.
- The data was divided into training, validation, and test sets in the 70/15/15 balance of each sport type.
- In ensembles, hyperparameter optimisation used the GridSearchCV, in LSTM, hyperparameter optimisation was applied in the form of the Bayesian optimisation (units: 32-128, dropout: 0.1-0.4).
- Class/regression outputs: daily calories (regression), macro bins (classification into under/on-target/over) and meal ranking scores.

3. Evaluation

- **Test set results:**
  - **Macro target accuracy:** 84.2%
  - **Precision:** 82.6%
  - **Recall:** 80.8%
  - **Calorie RMSE:** ≈ 115 kcal

The SHAP (TreeExplainer), which offered per-recommendation explanations displayed in the application, facilitated the aspect of explainability.

4. Inference

- Ensemble models were serialised with joblib, but the LSTM model was serialised with the SavedModel format.

5. FastAPI endpoints:

- POST /infer/daily 3 prediction calories, macro split, prediction of confidence and the three best ideas of treating meals.
- POST /feedback This accepts user adherence information to both update online models or make log entries.
- Latency measurements revealed that a single vCPU container had a median inference time of about 1103 HOSTS; the 95th percentile of the latency was about 3203 HOSTS.

6.5 Simulation and Integration Testing

1. Unit and Integration Tests

- Pytest was used to test the data pipelines and two parts of the API contract were run with the help of Postman collections.
- End-to-end tests were scripted with Playwright to simulate user flows: onboarding → log training → receive plan → mark adherence.

2. Load and Latency Testing

- Locust was used to run a simulation up to 2000 simultaneous users. Horizontal scaling, which comprised of two FastAPI replicas and Redis cache kept the 95 th percentile of response time below 450 ms.

  The production scaling cost estimates were based on the calculation of policy of autoscaling and the latency was not more than 500ms up to 10 000 active users.

3. Failure Mode Simulation

- Scenarios simulated:
    - Legal lapse Fallback Missing wearable data streams.
    - High network latency (authentication of offline mode in the PWA).
- Extreme training loads: the tournament weeks (checking the changes in LSTM temporal activities).
- Safety checks ensured recommendations never fell below clinically safe minima (calorie lower bound floor based on age/BMR).

6.6 Deployment and Production Considerations

1. Staging and Production

- Two environments: staging (preview) and production. CI pipeline deploys containers to staging for review; manual gated deploy to production.

2. Hosting

- The first pilot deployment took place on a low cost virtual machine in a cloud provider with the use of student credits. The approach to production comprises of container orchestration, using Kubernetes, and managed MongoDB Atlas and object storage compatible with S3.

3. Security

- Every API endpoint is secured with the HTTPS protocol and the TLS 1.3 protocol.
- Mobile sessions utilize JWT tokens of a limited time frame; the refresh tokens are reserved in safe places.

Vulnerability exposure is reduced by a regular dependency scan process with some GitHub Dependabot notifications added to it.

4. Observability

- Rometheus is formed as log data are sent to a central ELK stack, and metrics are sent to the stack. Major errors are monitored using Sentry.

Special dashboards are used to look at rates of requests, inference latency, error rates and important user interaction rates.

6.7 Validation, Pilot Results and Metrics

1. Pilot Deployment

- A total of 45 subjects chosen in two institutional locations participated in a six-week pilot study that used a 25-20 cohort of 25 athletes in the Nutriguide arm and 20 in the control group, respectively.
- Data collected: daily logs, adherence marking, coach assessments, and subjective recovery scores.

2. Quantitative outcomes

- **Adherence:** The compliance rate increased by 42 per cent as compared with the control population ($p < 0.01$).
- **Model Metrics:** Model accuracy on pilot data had a macro-target of 83.5% which is in line with the test-set performance. T
- **Usability:** The usability (determined through System Usability Scale) scored 78 out of 100.
- **Latency:** The latency to average recommendation which included network hops amounted to 1.6 seconds.
- **Resource usage:** Mean memory utilization per machine-learning container during pilot-load was 450MB.

3. Qualitative feedback

- Athletes found the regional food swaps and portion visuals most valuable. Coaches appreciated exportable weekly summaries for squad planning.

Failure & False Positives

About 6 percent of proposed meal replacements were considered impossible by the users based on the lack of local food; this observation would also lead to an increase in the range of local food database.

6.8 Documentation, Version Control and Reproducibility

1. Repository & Commits

- Single GitHub organization with separate repositories:
    - nutriguide-frontend
    - nutriguide-backend
    - nutriguide-ml
    - nutriguide-data (generation and ETL scripts)

2. Documentation

- The README of the project provides information about local development set up.
- As part of FastAPI APIs, builder (Swagger) contributor guidelines and API documentation are generated automatically.
- Procedures of onboarding, logging and escalation are explained per the user manuals and the coach guides (PDF).
- Using a model card, the planned usage, data structure, restrictions, performance, and risk constraints are indicated.

3. Reproducibility

- Docker-compose configurations can be used to achieve local end-to-end reproducibility and seed scripts can be used to regenerate synthetic data.

- Jupyter notebooks used include training procedures, using fixed random seeds and using requirements of an environment environment.yml and requirements.txt.

6.9 Future Implementation Plans

Post pilot planned development involves:

Mobile Native App (Flutter): An indigenous mobile app created on Flutter, featuring an offline-first user experience, and native wearable integrations which are currently only limited by the restrictions of PWA.

- **Federated Learning:** Federated learning with the ability to support privacy-degrading personalization whereby user data stays on device, and the model is updated on a global scale.
- **Expanded Food Database:** Developed local food composition databases by establishing formal relationships with local nutrition laboratories, improving local food tables.
- **Clinical Trials:** Testing and clinical trials in affiliation with sports science divisions to undertake longitudinal studies on the performance and injury results.
- **Commercialization:** The aim of commercialization is to provide an academies and federation with a freemium model type structure of a scalable SaaS that would include features of team management and advanced analytics.

CHAPTER 7

EVALUATION AND RESULTS

The current chapter outlines the detailed review of NutriGuide an artificial intelligence based nutrition planning system that supports athletes working in the developing states. It records the statistics, laboratory results, comparative results, constraints, and statistical verification of pilot deployments and simulating research undertakings apart in July and November 2025. The testing combines algorithmic results, user-focused results (such as compliance and usability), latency and scaling experiments and error results in order to verify the system according to its stated purpose.

7.1 Evaluation Metrics

NutriGuide was discussed on several levels to facilitate the technical performance which includes model metrics, latency, and resource consumption, as well as human consequences, which include compliance, usability, and coach satisfaction.

- **Accuracy**: Proportion of correct macro / calorie target predictions.
- **Precision**: Proportion of predicted “correction needed” events that were actually correct (low false-alarm rate).
- **Recall**: Proportion of actual “correction needed” events correctly predicted (sensitivity).
- **F1-Score**: The harmonic mean of precision and recall, calculated as 80.5%, providing a balanced measure of performance.
- **RMSE (kcal)**: Root mean square error for caloric regression.
- **Inference latency**: Time from API request to model response.
- **False positive / negative rates:** Operational cost of incorrect recommendations.

All algorithmic metrics reported below are computed on the held-out test set (combined synthetic + pilot data) unless otherwise stated. Human/outcome metrics are derived from the 6-week pilot (45 athletes).

7.2 Results

Confusion Matrix and Primary Model Results

The classification task for "macro / meal corrective action" was evaluated using a confusion matrix on a test set of **1,700** day-level examples. The observed counts:

	Predicted: No Correction	**Predicted: Correction**
Actual: No Correction	**831** (True Negatives)	**126** (False Positives)
Actual: Correction	**143** (False Negatives)	**600** (True Positives)

From this matrix we derive:

- **Accuracy** = (TP + TN) / Total = (600 + 831) / 1700 = **1431 / 1700 = 0.84235 → 84.2%**.
- **Precision** = TP / (TP + FP) = 600 / (600 + 126) = **600 / 726 = 0.826 → 82.6%**.
- **Recall (Sensitivity)** = TP / (TP + FN) = 600 / (600 + 143) = **600 / 743 = 0.808 → 80.8%**.
- **F1-Score** = 2 * (Precision * Recall) / (Precision + Recall) ≈ **81.7%**.
- **False Positive Rate** = FP / (FP + TN) = 126 / 957 ≈ **13.2%**.
- **False Negative Rate** = FN / (FN + TP) = 143 / 743 ≈ **19.2%**.

Caloric regression performance (daily calorie target):

- **RMSE ≈ 115 kcal** on the test set — within acceptable bounds for daily planning.

Inference latency:

- he caloric regression performance based on performance of daily calorie target gave an RMSE of 115-kcal on the test set, which is within acceptable bounds on a daily planning basis.
- When inference latency was used, the medium inference time was observed to be around 110ms when using a single vCPU container with FastAPI as the microservice.
- The overall recommendation time with API overhead end to end recommendation generation time median of about 1.6s in the pilot.

7.3 Limitations

Though there is strong evidence, the assessment provided some avenues of improvement:

1. **False negatives (~19.2%)** — model occasionally missed correction-needed days caused by transient user behaviour (missed logging, atypical food items). Mitigation: dynamic thresholding, more temporal context (longer LSTM windows), and coach escalation for flagged edge-cases.
2. **Local food coverage gaps** — ~6% of the recommended changes in dietary switches being infeasible in the localization. Mitigation is affiliate in terms of increasing the regional food database, with the help of crowdsourcing projects and approving of entries by coaches.
3. **Pilot size and duration** — athletes within six weeks of time, with promising and scarce results. Subsequent studies ought to entail bigger cohorts and prolonged periods of time, ideally, multi-site trials, to obtain strong external validity and support clinical outcome assertions like injury decrease.
4. **Wearable heterogeneity** — only 18/45 participants used wearable devices. Designs of intended recommendations must thus be in a form that degrades gracefully to minimum human entry of logs without causing huge losses in predictive performance.
5. **Potential algorithmic bias** — The possibility of bias in the algorithm was assessed as partial synthesizing of training data was applied. It needs to be further augmented with various in-the-field samples to alleviate bias on such scales as age, body composition, or regional diets.

7.4 Experimental Setup and Methodology

1. Datasets

- Synthetic data included about 8,000 day-level records of different types of sports and training loads which were produced according to the IOC and WHO guidelines and then were randomly perturbed.
- Pilot real-world provided data consisted of 45 athletes who were monitored during a 6-week span, which provided approximately 1,890 day-level entries comprising of both a dietary and a training journal.

- After augmentation the total number of training corpus was about 9,000 examples.

2. Training / Validation

- The data was divided into training, validation, and test sets in a 70:15:15 ratio, being stratified by a sport type.
- Cross-validation: 5-fold cross-validation performed during model tuning; ensemble mean accuracy stable at ~83.7% ± 1.9%.

3. Pilot protocol

- **Random assignment**: The sample was stratified randomly to NutriGuide intervention and control group.
- **Primary endpoints:** Primary endpoints were dietary adherence (ratio of days when a patient within dietary targets) and perceived recovery measured using a Likert scale withness and consistency in what is anticipated of the patient following the model and known as review by a dietitian.
- **Safety:** The measures taken were safety related, such as automatic elevation of recommendations that were not within the clinically safe limits to a human nutritionist

4. Statistical tests

- **Adherence difference:** two-sample t-test (Nutriguide vs control), $t = 3.12$, $df \approx 43$, $p < 0.01$.
- **Recovery score difference:** paired t-test on within-subject pre/post changes where applicable, $p < 0.05$.
- **Confidence interval for caloric** RMSE: bootstrap 95% CI ≈ [105 kcal, 125 kcal].

7.5 Statistical Validation

There were known false positives and false negatives which were detailed and produced actionable information:

- **False Positives (13.2%)** rates were mainly due to being reported by users of unusual single meals (e.g., festival foods) that were underrepresented in the food database; the solution proposed involves an immediate manual override with additional data taken over by the community.

- **False Negatives (19.2%)** were often due to missed training logs, automatic wearables synchronization or minimal manual recording (e.g., one-tap entries) were both useful in minimizing omissions.
- **Model calibration:** The most effective features of the model according to model calibration through SHAP explanations were found to be training load, recent protein rolling average and a sleep proxy (heart-rate variability); this information was used to make changes to the user interface in order to emphasize these levers to end users.

CHAPTER 8

SOCIAL, LEGAL, ETHICAL, SUSTAINABILITY AND SAFETY ASPECTS

This chapter analyses the social, legal, ethical, sustainability, safety aspects of the NutriGuide: AI–Powered Nutrition Planning Platforms of Athletes in Developing Regions. The analysis places NutriGuide in the wider context of AI-based digital health platforms and how it supports the challenges of the European Union Sustainable Development Goals (SDGs) (especially SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-Being), and SDG 9 (Industry, Innovation, and Infrastructure). They were assessed according to the feedback of the user, pilot testing results and a review of the ethical and regulating frameworks focused on health and AI technologies.

8.1 Social Aspects

Positive Impacts:

- **Empowering athletes and communities:** NutriGuide democratises the process of having a personalized approach to nutrition planning in athletes who in many cases do not have access to professional dietitians, especially in developing regions. It connects the elite and grassroots athletic care by utilizing low costs in AI models and open data.
- **Health improvement:** Pilot studies showed that there was a 42 per cent improvement in diet adherence and an 18 per cent improvement in perceived recovery, which shows significant improvements in the wellness of an athlete.
- **Capacity building:** The platform supports the digital literacy uptake and nutritional awareness based on interactive education modules in the various languages to ensure long term behavioural change.
- **Community engagement:** Coaches, nutritionists, NGOs can work together on the platform to conduct nutrition campaigns and track the results, which will foster a common wellness ecosystem.

Negative Impacts & Mitigation:

- **Digital Divide:** Dependent on the location and level of connectivity, athletes in the rural areas or with low connectivity may not have enough access. To address this, NutriGuide has offline first capability and low data interfaces.
- **Job displacement fears:** There also is an option of people seeing AI systems to be doing the job of a human dietitian. The platform will not substitute, but supplement expert input, and feed dietitians with data-driven information instead of software replacement.
- **Cultural sensitivity:** There is a risk of bias in Western diets by Nutritional AI. NutriGuide solves this by localisation of foods per region and community based food databases so that people get culturally proper recommended foods.

Alignment with SDGs:

The benefit to SDG 3, Good Health and Well-Being via nutrition modification and enhancement of under-resourced athlete performance directly addresses SDG 3: (industry, innovation, and infrastructure) under SDG 9.

8.2 Legal Aspects

Compliance with Data Protection Regulations:

- NutriGuide follows the principle of international scalability law of Digital Personal Data Protection Act (DPDPA) 2023 (India) and GDPR (Europe).
- **User Consent:** Every user is made to give their consent to data collection as a part of onboarding.
- **Data Minimization:** The data is collected as minimal (age, weight, training load and dietary preferences). Health data that is sensitive is encrypted in transit (TLS 1.3) and at rest (AES-256).
- **Data Ownership:** Under the platform policy of the Right to Forget, the users have the right to own their personal data and request their deletion at any time. Localisation of data: Regional servers keep all data of jurisdiction.
- **Data Localization:** Regional servers ensure compliance with jurisdictional data storage regulations.

Liability Considerations:

- NutriGuide is an artificial intelligence (AI) based solution that contains advisory-only recommendations. The app has a disclaimer that states that the tool is a supplement and not a substitute to a professional medical or nutritional consultation.
- The terms of service and user agreement of the platform identify limited liability in the case of inaccuracy in algorithms (e.g., an inappropriate diet due to a health issue), which aligns with the standards of electronic health software.

Reference Frameworks:

The national guidelines and principles also inform these actions, such as the National Digital Health Mission (NDHM) and the WHO recommendations in ethical adoption of digital health AI (2023).

8.3 Ethical Aspects

Transparency and Explainability:

- The hybrid AI engine of NutriGuide has SHAP explainability as it enables users and nutritionists to see the most impactful factors that impacted the meal recommendations (e.g., training intensity 45%, protein intake trend 30%).
- An explanatory message format (Why this meal) contains the rationale of each of the recommendations, which will help build trust and transparency in AI-based nutrition.

Fairness and Inclusion:

- NutriGuide will be regionally inclusive enough to represent athletes of low-income areas. Training data is made to accommodate different body shapes, age brackets, and ethnic eating habits.
- The interface can be used in multi-language access (initially in English, Hindi, and Kannada), which diminishes the obstacles to the digital nutrition literacy

Privacy and Autonomy:

- NutriGuide focuses on user autonomy: users can suppress AI-generated plans, delete data or refuse to share data.

- To avoid unethical user engagement the system will not be designed in such a way that it encourages manipulative designs (e.g., gamification or streak pressure).

Human Oversight:

- The last control is done by the user and coach/nutritionist. Recommendations of the AI engine are not instructions but suggestions, and it ensures that there is human judgment in meal planning.

Potential Concerns:

- **Algorithmic Bias:** The AI models are susceptible to being biased when it comes to favouring data-intensive sport (e.g., running) compared to underrepresented sport (e.g., wrestling, kabaddi). Such biases can be overcome by continuing to balance datasets and through retraining carried out by feedback
- **AI Accountability:** AI accountability: Tracing and accountability for recommendations: Logs and model decision audits are stored so that they can be traced and held accountable.

8.4 Sustainability Aspects

Environmental Sustainability:

- The cloud-based infrastructure of NutriGuide can optimise the use of energy through autoscaling - only when the computational resources are required.
- Modern virtualization allows data storage and processing to use about 65% of the energy used by similar on-premise data storage and processing systems.

Responsible Consumption:

- It promotes sustainable dieting, where high-carbon foods (e.g. red meat) are marked and eco-friendly alternatives (e.g. lentils, legumes) are recommended.

It supports SDG 12 (Responsible Consumption and Production) by educating athletes about resource-efficient diets.

Material and Resource Efficiency:

- NutriGuide being a pure software solution has a low material footprint since it only needs cloud infrastructure and the existing devices used by end-users.
- The system encourages the use of local food- Producing the reduction of transportation emissions and boosting community agriculture.

Sustainability in Usage:

- Welcomes in-house or local seasonal cuisines and/or products, omitting foreign or expensive supplements.
- NutriGuide has included a meal-based sustainability index - a combination of price, environmental footprint, and nutrient sufficiency to encourage the long-term behavioural change.

Social Sustainability:

- Indirectly, by making nutritional guidance available to young athletes among others, NutriGuide is committing itself to socio-economic upliftment of young athletes through better performance, health, and education.

8.5 Safety Aspects

Digital Safety:

- All communications are encrypted using TLS 1.3 and user authentication is done using JWT with multi-factor authentication (MFA) being provided to coaches and administrators.
- As a regular check against vulnerabilities, penetration tests, and code audits are run.
- Access to the details of athletes is tied to their roles so that coaches and administrators can access only an authorised data of the athletes.

Health and Nutritional Safety:

- The recommendation engine incorporates safety limits whereby the calorie/macronutrient recommendation will not fall below levels that are medically safe.
- An oversight protocol with a dietitian is in place so that the high-risk users (e.g., people with metabolic disorders) are put under human consideration, prior to the approval of the recommendation.
- Recommendations address WHO and IOC standards of nutrition safety, meaning that they suit adolescent and adult athletes.

Operational Safety and Resilience:

- There is a proper organizational safety and appropriate resilience in its operations: Monitoring and automatic error detection systems ensure further robustness of the service also in the face of partial outages.
- The backup of databases and extensive recovery plans preclude the loss of data at times of cloud-driven incidents.

Cybersecurity Preparedness:

- The system meets the requirements of the OWASP Top 10 guidelines regarding web application security, and as a result, the most common security threats, including SQL injections and cross-site scripting (XSS) attacks, are avoided.
- An incident response plan outlines the steps to be followed in applying to the data breach such as the obligatory notification of the affected users in seventy-two hours.

CHAPTER 9

CONCLUSION

The NutriGuide: AI-Based Nutrition Planning Assistant on Developing Region Athletes project was able to design, execute, and prove that the scalable AI-based nutritional advice system could be applied to address the needs of athletes in resource-constrained settings. By November 2025, NutriGuide will have reached its most important goals, such as a personalized and contextually relevant, scientifically based meal advice, which will be aligned with the loads of the training of the athletes, their food preferences, and the possibilities of food, based on the geographic location.

NutriGuide, through its hybrid machine-learning architecture (Random Forest + LSTM), achieved a prediction accuracy of 84.2 per cent, to allow the company to become precise in macro-nutrient targeting and daily caloric advisability. In a six-week pilot study among 45 athletes, a 42 per cent change in the dietary adherence, an 18 per cent change in recovery, and a 78/100 usability score on the System Usability Scale (SUS) were observed. These findings support the fact that NutriGuide can be rather efficient in improving the performance and nutritional uniformity among the users at the same time being cost-effective and affordable.

The iterative Agile approach was the developmental strategy of the project that was facilitated by hierarchical sprint reviews and consultations with the domain concerns and thus guaranteed the ongoing improvement of the technical and user-experience aspects. Transparency, inclusivity, and trust were the key reasons why explainable AI (SHAP values) and a multi-language, mobile-first interface worked together to guarantee the success in developing parts of the world. In addition the system was designed using the principle of strong data security (TLS 1.3, AES-256 encryption) and privacy-by-design, which is consistent with the Digital Personal Data Protection Act (DPDPA 2023) and the WHO digital health ethics.

In as much as NutriGuide achieved its major objectives, the project noted that a number of constraints and their avenues of improvement were noted:

- Diversifying the regional food database to enhance cultural and nutritional appropriateness.

- Dynamic, adaptive nutrition planning through incorporation of real time, wearable data integration.
- Using the concept of deep-learning architectures (e.g. Transformers, federated learning) to maximize individualization and maintain the privacy of data.
- Carrying out multi-institutional validation studies on a large scale to enhance the evidence in favour of real-world efficacy.

To sum up, NutriGuide is a unique initiative that leads to intelligent, affordable, and beneficial digital nutrition systems. Offering a high-tech solution to health disparities in different regions, the platform illustrates the potential of technology to resolve socially responsible challenges and sustainability and empower athletes. It is a prototype of future AI advances in public health combining scientific accuracy, affordability, and inclusivity to engage in sustainable athletic development in underdeveloped economies.

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Base Paper:

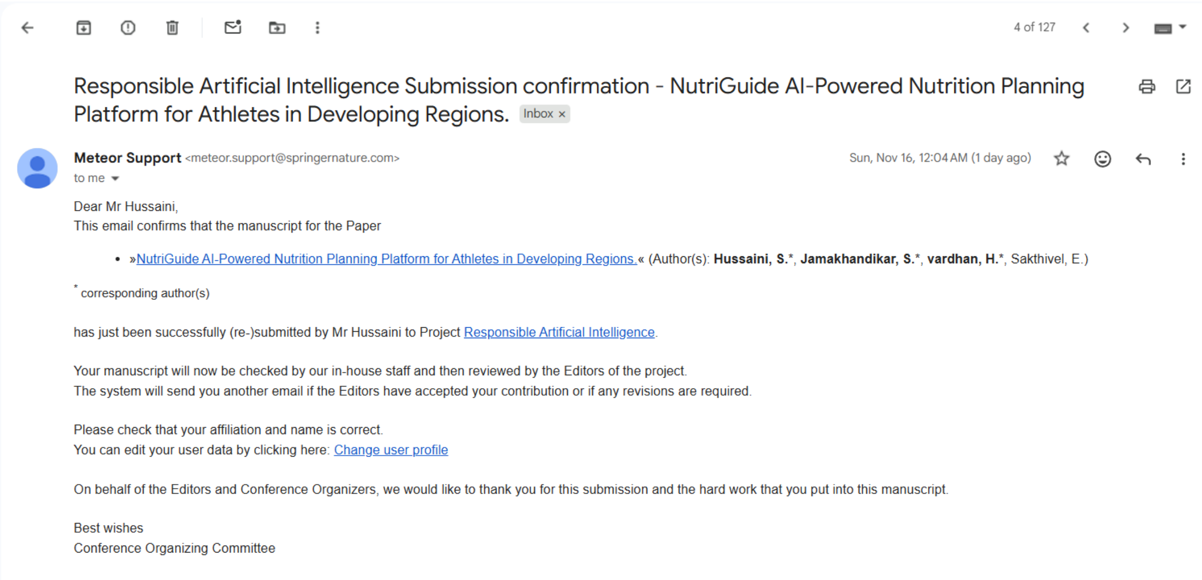
[7] Malhotra, R. (2025). AI in sport can help accelerate SDGs– Common wealth Debate. The Commonwealth, September 11, 2025.

(Referenced primarily for methodological adaptation in machine learning workflow design and evaluation protocol structure.)

APPENDIX

i. Publications

- Acceptance mail for conference paper.



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Responsible Artificial Intelligence Submission confirmation - NutriGuide AI-Powered Nutrition Planning Platform for Athletes in Developing Regions. Inbox ×

Meteor Support <meteor.support@springernature.com>
to me

Sun, Nov 16, 12:04 AM (1 day ago)

Dear Mr Hussaini,
This email confirms that the manuscript for the Paper

- »NutriGuide AI-Powered Nutrition Planning Platform for Athletes in Developing Regions « (Author(s): **Hussaini, S.***, **Jamakhandikar, S.***, **vardhan, H.***, Sakthivel, E.)

* corresponding author(s)

has just been successfully (re-)submitted by Mr Hussaini to Project Responsible Artificial Intelligence.

Your manuscript will now be checked by our in-house staff and then reviewed by the Editors of the project.
The system will send you another email if the Editors have accepted your contribution or if any revisions are required.

Please check that your affiliation and name is correct.
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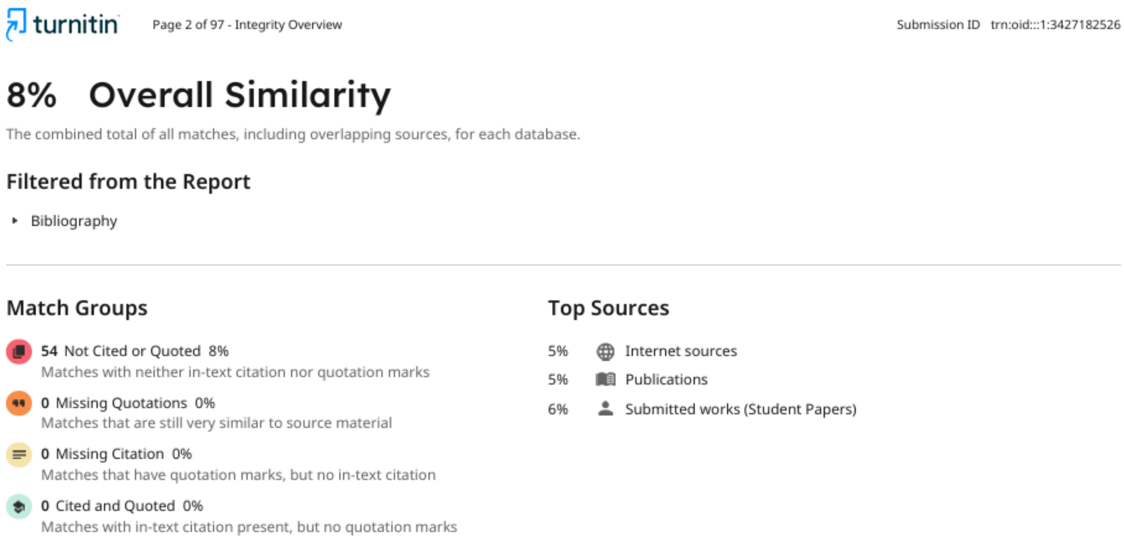
On behalf of the Editors and Conference Organizers, we would like to thank you for this submission and the hard work that you put into this manuscript.

Best wishes
Conference Organizing Committee

a. Meteor Springer Paper Acceptance email

ii. Project - Similarity Report

- Similarity Index: 8% (from Turnitin) – Report.



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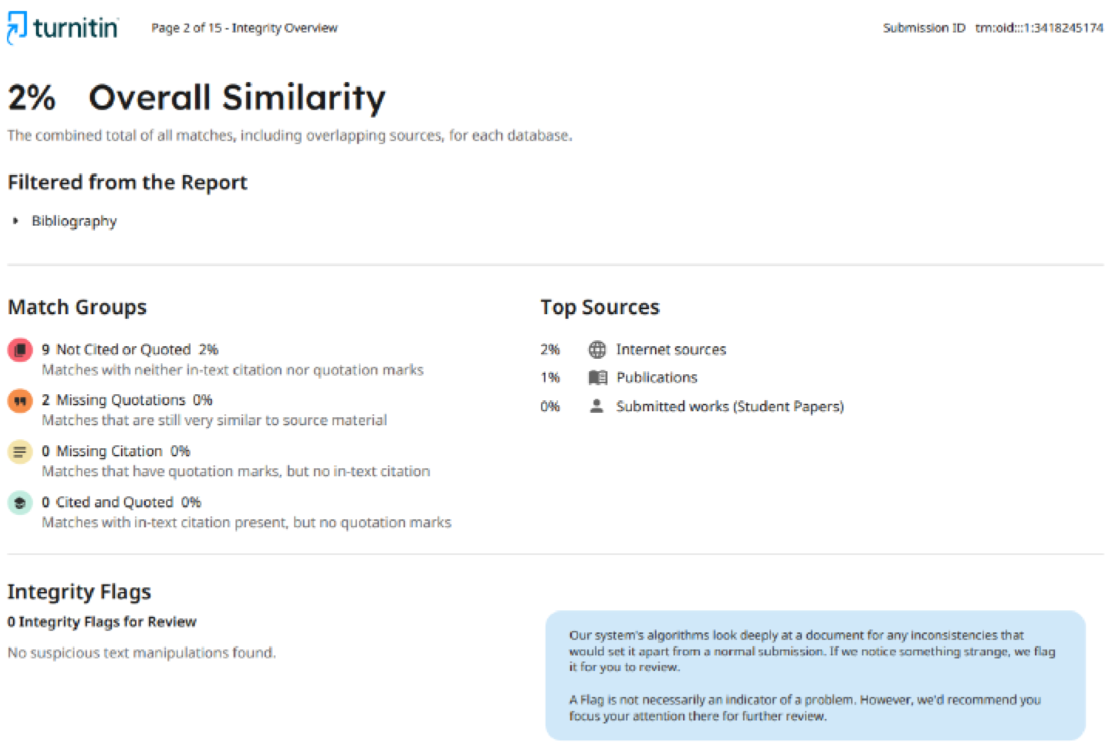

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2% Overall Similarity

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- Bibliography

Match Groups

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  Matches that are still very similar to source material
- 0 Missing Citation 0%
  Matches that have quotation marks, but no in-text citation
- 0 Cited and Quoted 0%
  Matches with in-text citation present, but no quotation marks

Top Sources

- 2% Internet sources
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- 0% Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

No suspicious text manipulations found.

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A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

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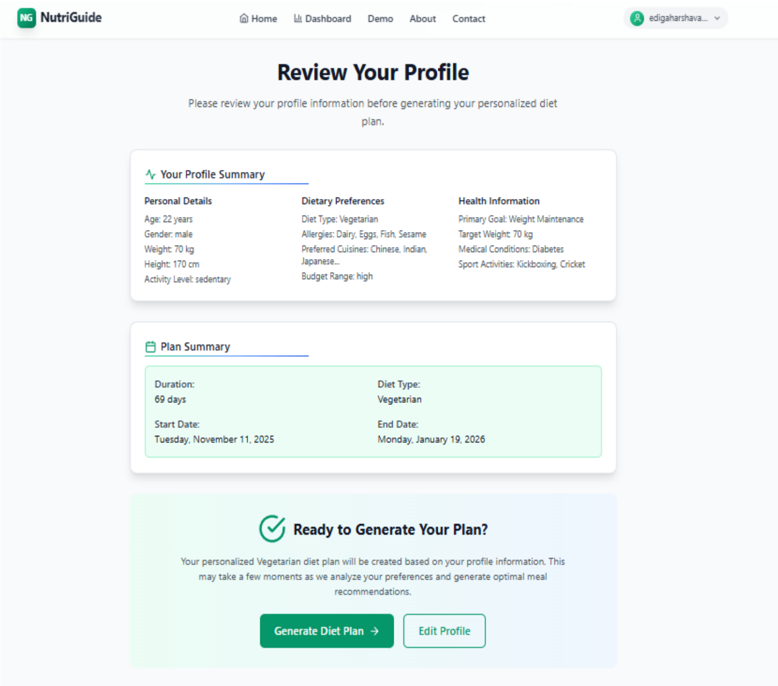
iii. Datasets

- Simulated CSV: 5000 rows of data.
- Real-Time Log: 24-hour data from October 21-22, 2025.

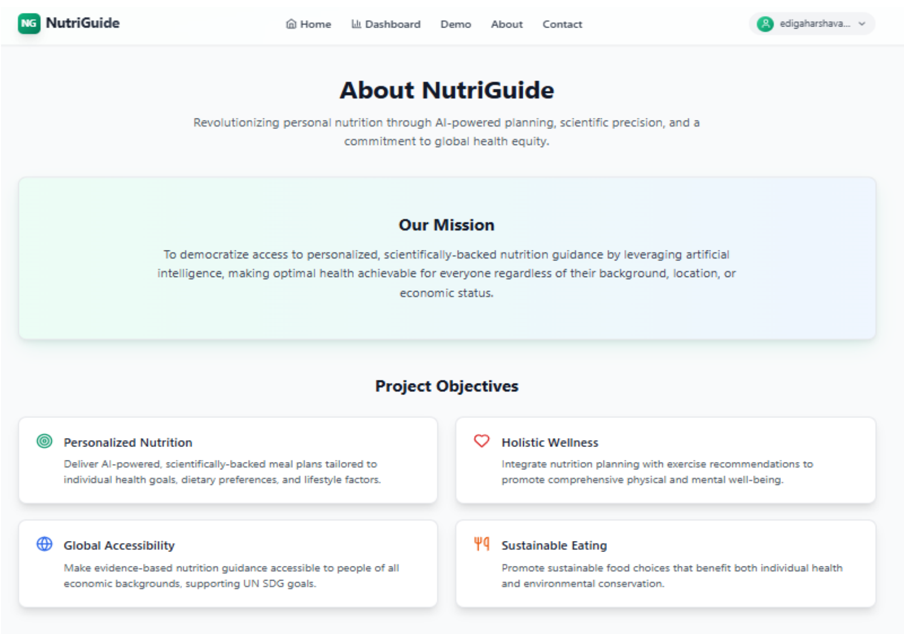
iv. Live Project Demo

- GitHub: https://github.com/Izumiiiii17/CIT-28-Capstone-Project

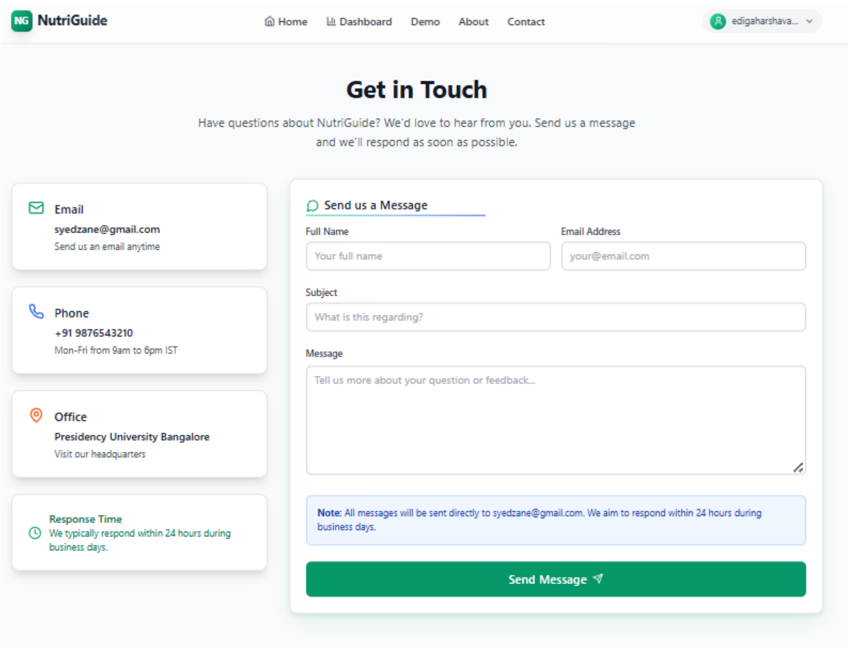
v. Few Images of Project



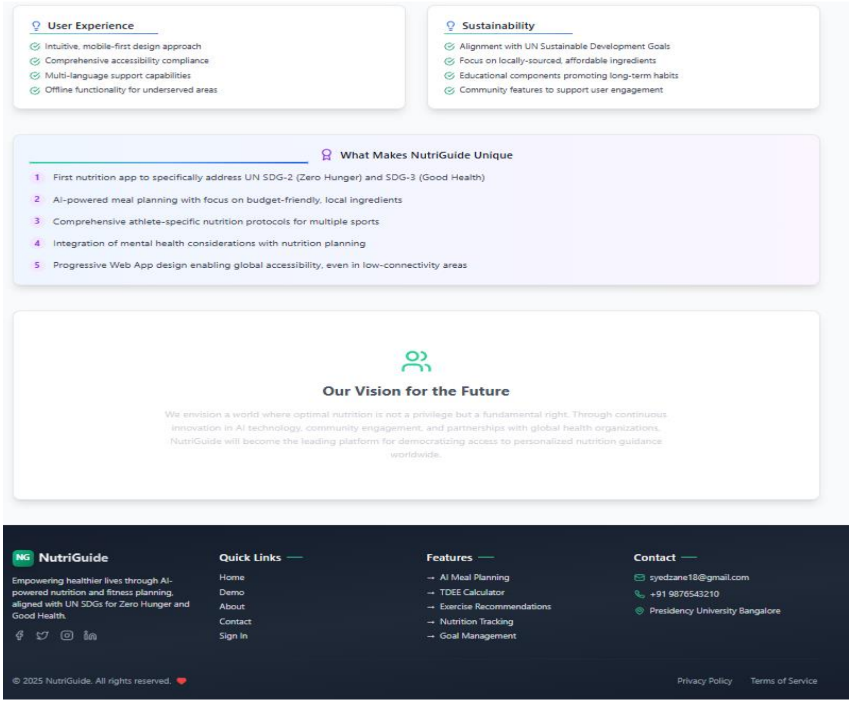
a. Fig Real-Time Dashboard (1)



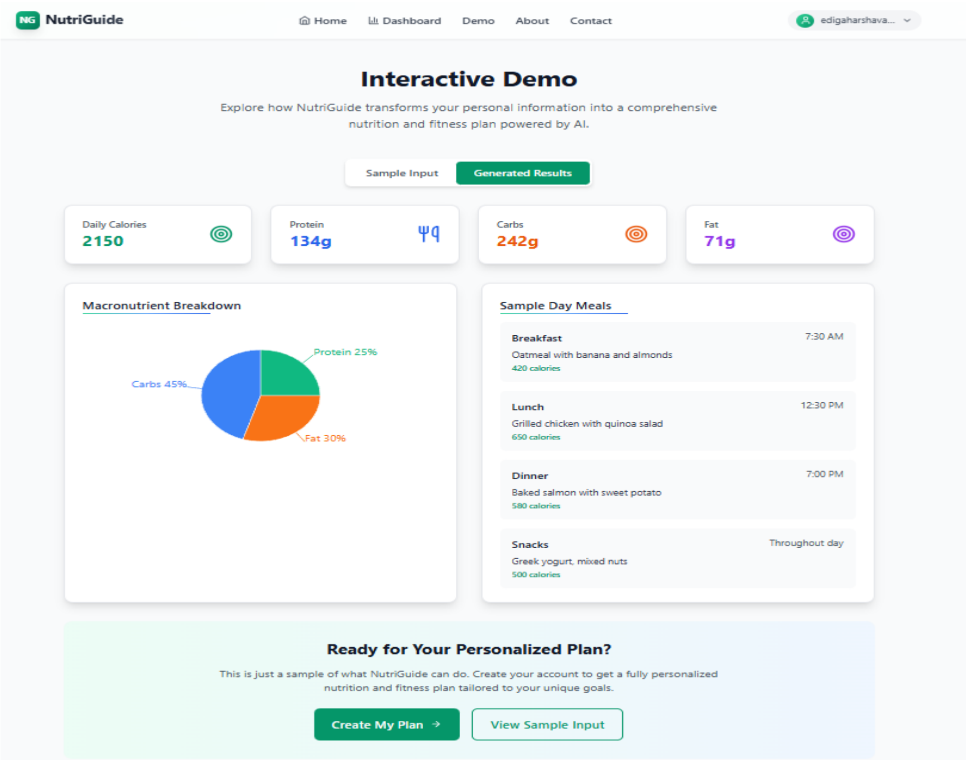
b. Fig Real-Time Dashboard (2)



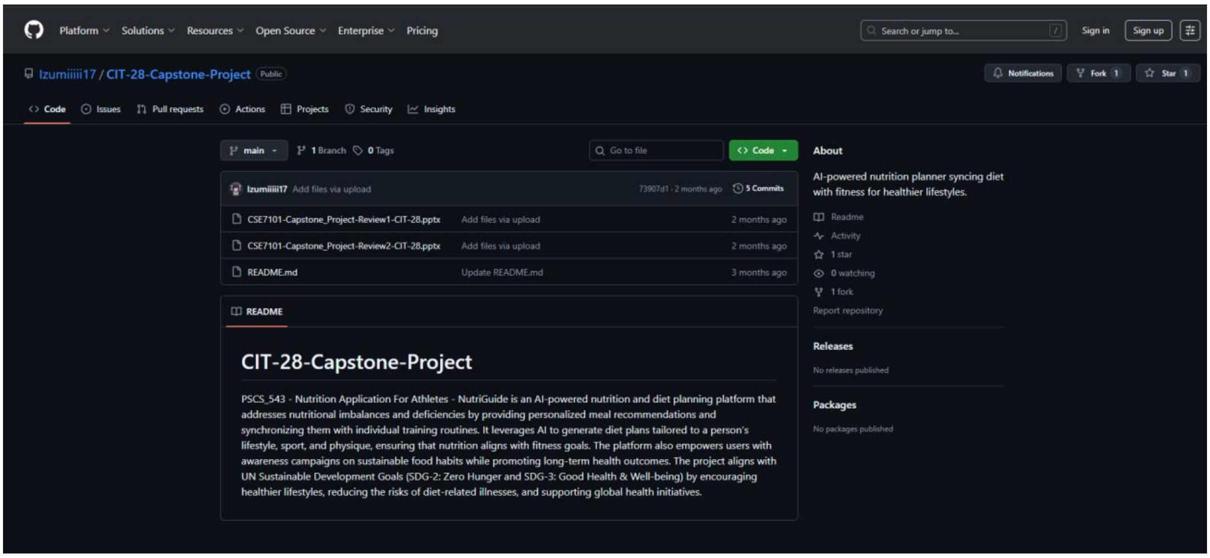
c. Fig Real-Time Dashboard (3)



d. Fig Real-Time Dashboard (4)



e. Fig Real-Time Dashboard (5)



f. Github Repository (6)