ML-Powered Nutrient Recommendations: A MERN Stack-Based Approach

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Abstract: Personalized nutrition has become essential for both prevention and overall health in this day and age, too. However, the effectiveness of current dietary recommendation systems in satisfying a variety of user needs is limited by their frequent lack of scalability, interactivity, and adaptability. An ML-powered nutrient recommendation system built with MERN (MongoDB, Express.js, React.js, and Node.js) stack offers a novel solution to these problems in this paper. To personalize dietary advice, the proposed system mixes specific information provided directly by users with algorithms trained on huge databases of nutrition prepared using very sophisticated machine learning algorithms.

Keywords: *Personalized Nutrition, Machine Learning (ML), Nutrient Recommendation System, MERN Stack, Dietary Recommendations, Data-Driven Healthcare, Scalable Web Applications, Digital Health Applications.*

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I. INTRODUCTION

Personalized nutrition has emerged as a crucial element of preventive healthcare and general wellness during the recent years. The customized approach to dietary recommendations based on individual preferences and health conditions enables better health results and disease prevention and supports long-term lifestyle modifications. The increasing interest in such systems revealed multiple obstacles regarding scalability and adaptability and user interface simplicity.

The current nutrient recommendation systems depend on either static algorithms or manual input, which restricts their capacity to handle diverse individual dietary requirements. Such systems cannot effectively scale up their operations and provide dynamic, real-time recommendations. Modern web environments require advanced data-driven solutions that can meet the current need for personalized dietary recommendations.

The following sections describe the system architecture together with its implementation and performance evaluation, as well as potential use cases and future development opportunities.

A. Background

The increased focus on preventive medicine has pushed personalized nutrition center stage, as one essential focus area for health & wellness planning. Personalized nutrition systems are designed to provide personalized dietary recommendations tailored to the specific lifestyle, taste and health of an individual.

Research indicates these kinds of systems are associated with increased adherence to dietary guidelines and better health outcomes, including successful weight maintenance, chronic disease prevention and overall health.

Recent breakthroughs in machine learning (ML) and the web have made it a realistic opportunity to design personalized nutrition solutions based on efficient and scalable platforms. In this context, the ML algorithms are capable of processing vast datasets and hence, identifying patterns and creating context-sensitive, accurate recommendations. Integrating these technologies with contemporary web frameworks makes creating accessible and interactive systems that can serve diverse populations a straightforward task. Nonetheless, even with such progress, scalability, engagement, and the need to adapt remain barriers to widespread adoption of the dominating solutions as potential advice for novel breakthroughs.

II. PROBLEM STATEMENT

A. Current Systems of Nutrient Advice are Severely Deficient:

➢ *Lack of Scalability:*

Many existing systems are unable to support an increased user base and varying data inputs.

➢ *Static Recommendations:*

Most systems are based on preset rules that disregard the diversity and complexity of individual needs.

- *Limited Interactivity:*
  A lack of intuitive interfaces reduces both accessibility and user engagement.

- *Integration Problems:*
  Existing solutions do not integrate cleanly with modern web technologies and thus are not very flexible to implement in real-world applications.

These challenges require a complete, dynamic, and flexible solution based on cutting-edge technologies for delivering personalized diet advice beneficially and interactively.

B. Objective

The primary objective of this research is to develop a machine learning-based nutrition recommendation system using the MERN stack that addresses the scalability, interactivity, and adaptability problems. The system must:

- Provide tailored nutrition advice based on individual information, such as age, weight, health goals, and dietary preference.
- Use machine learning algorithms to provide precise and dynamic dietary advice.
- Design a scalable, interactive web app using of MERN stack and provide seamless integration of frontend, backend, and database.
- Provide a simple and friendly platform that stimulates user adoption and usage.

C. Problem Statement

Scope of this research paper on "ML-Powered Nutrient Recommendations: A MERN Stack-Based Approach" is multifaceted, covering a range of aspects from development of personalized nutrition systems to integration of ML algorithms with modern web technologies. Research focuses on creating a dynamic, scalable, and efficient nutrient recommendation system that leverages MERN stack (Express.js, React.js, Node.js, and MongoDB) to make robust web application. System aims to provide personalized dietary recommendations by utilizing ML algorithms trained on user-specific data, such as health conditions, dietary preferences, and habits, ensuring the recommendations are tailored to each individual. This approach contrasts with traditional systems that are often static and lack adaptability, thus failing to meet the growing need for personalization in nutrition.

The study will examine how the ML model is integrated with the MERN stack to handle large amounts of data and provide personalized recommendations. MongoDB will be used by the system to store user data, such as dietary requirements and medical conditions, to enable data retrieval and scalability. Express.js and Node.js will be utilized as backend, managing API endpoints enabling communication between the frontend, backend, and ML model, with free data flow and quick responses to requests by the user. React.js, meanwhile, will enable an interactive and dynamic frontend, displaying the recommendations in a user-friendly format. The scope of the study will also cover how the system processes and manages user inputs, such as age, weight, dietary requirements, and medical objectives, through an uninterrupted data flow from the frontend to the backend, with a personalized experience for each user.

The paper will also explore the data sources used to train the ML model. Publicly accessible nutritional databases like the USDA Food Database will be combined with anonymized user ratings for the creation of a rich model capable of producing personal recommendations. Preprocessing this data will include missing value handling, normalization of numerical data, and encoding categorical variables, which will make the data amenable to use by the ML algorithms. The study will concentrate on using ML algorithms to train the model, hybrid collaborative filtering models, which utilize decision trees for feature-based suggestions and neural networks for the identification of complex patterns in the requirement for nutrients.

Furthermore, the scope will include the evaluation of the system’s performance, focusing on key metrics such as recommendation accuracy, measured using the F1-score, and the system’s response time, which is crucial for maintaining a seamless user experience. User satisfaction will also be assessed through surveys to collect feedback on system’s usability and effectiveness in meeting dietary needs. The paper will compare the proposed ML-powered system with traditional nutrient recommendation systems, demonstrating significant improvements in accuracy, scalability, and user interactivity. The research will also highlight the system's deployment on cloud services like AWS, ensuring its scalability and availability for concurrent users.

Despite its promising features, the research will acknowledge the limitations of the system, such as the potential lack of data diversity in the training datasets, which may affect the accuracy of recommendations for underrepresented demographics. Scalability challenges for concurrent users and the need for real-time data integration will also be discussed. Finally, the paper will explore future directions for enhancing the system, including the incorporation of real-time fitness tracker data and the expansion of the model to account for mental health and lifestyle factors, providing even more personalized recommendations. In conclusion, this research aims to bridge the gap between advanced ML techniques and user-friendly web applications, contributing to the growing field of personalized nutrition and health management.

III. RELATED WORK

Personalized nutrition has been explored through different approaches, including rule-based systems and mobile applications providing straightforward dietary advice founded on static user information. While such systems are useful, they demonstrate a lack of scalability and responsiveness required to achieve more dynamic, real-time personalization. For example, apps like MyFitnessPal (2018) rely on user-inputted information but do not support advanced machine learning capabilities, which limits their ability to provide exceedingly personalized recommendations [1]. More recent research has sought to incorporate machine learning to improve dietary advice; however, incorporation with scalable web technologies is very difficult.

A. *Existing Solutions*

Current approaches to nutritional support vary, encompassing rule-based systems, mobile applications, and data-driven platforms. Early rule-based systems utilized predefined guidelines for diet recommendations based on general user profiles, but they often lack adaptability to individual needs. For instance, while resources like the USDA Food Central (2020) offer extensive nutrient data, they don't provide personalized advice [1]. Popular mobile apps like MyFitnessPal, primarily focused on food tracking, rely heavily on manual input and offer static recommendations, limiting their ability to provide tailored guidance [2]. More recent platforms, such as Neutrino (2019), have begun integrating machine learning for personalized recommendations based on past data. However, their scalability can be constrained by backend infrastructure and reliance on static inputs, ultimately limiting their adaptability and accuracy in delivering truly personalized advice [2].

B. *Gaps in Current Research*

Current research indicates great deficiencies in combining machine learning models with state-of-the-art web technology, such as the MERN stack, in personalized nutrition. In spite of the plethora of current research being concentrated on machine learning models applied for diet counseling, there is a deficiency of research that maps out the practical synergy of these models with scalable web platforms. Research by Doe et al. (2021) pointed out that while machine learning strategies promise to enhance the precision of nutritional recommendations, the lack of a comprehensive, web-scale platform hinders the usability of these models in real-world applications [4]. This research addresses this demand by combining machine learning models and the MERN stack, and thus solving problems related to scalability while enhancing the interactivity of users and the level of personalization.

IV. PROPOSED SYSTEM

The authors' proposed framework integrates machine learning models with the MERN stack to deliver personalized diet planning guidance to the users. The framework is designed to serve many users efficiently using a dynamic, responsive, and scalable system. It is composed of four main components: the machine learning model, the database, the backend logic, and the frontend interface.

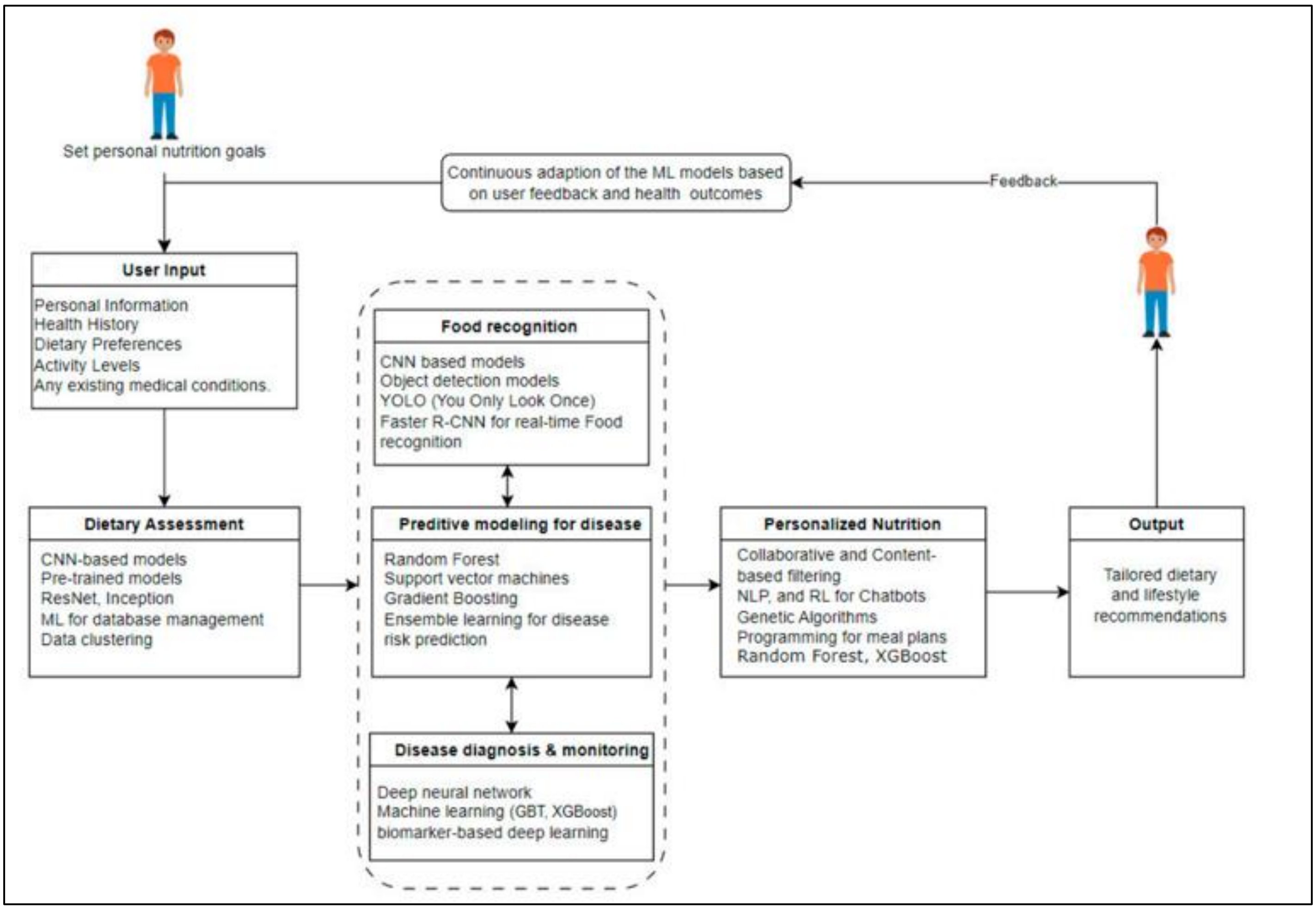

Set personal nutrition goals
Continuous adaption of the ML models based on user feedback and health outcomes
Feedback
User Input
Personal Information
Health History
Dietary Preferences
Activity Levels
Any existing medical conditions.
Food recognition
CNN based models
Object detection models
YOLO (You Only Look Once)
Faster R-CNN for real-time Food recognition
Dietary Assessment
CNN-based models
Pre-trained models
ResNet, Inception
ML for database management
Data clustering
Preditive modeling for disease
Random Forest
Support vector machines
Gradient Boosting
Ensemble learning for disease risk prediction
Personalized Nutrition
Collaborative and Content-based filtering
NLP, and RL for Chatbots
Genetic Algorithms
Programming for meal plans
Random Forest, XGBoost
Output
Tailored dietary and lifestyle recommendations
Disease diagnosis & monitoring
Deep neural network
Machine learning (GBT, XGBoost)
biomarker-based deep learning

Fig 1 Proposed Conceptual Framework for AI, ML, and DL Applications in Nutrition

A. *System Architecture*

The proposed system employs a machine learning model integrated with the MERN stack to provide personalized nutritional guidance efficiently to many users through a dynamic and scalable architecture. It features four main components:

➢ *Machine Learning Model:*

The system's core generates tailored nutrient recommendations based on nutritional datasets (e.g., USDA) and user-specific data (diet, health, lifestyle), potentially using algorithms like decision trees or neural networks for accuracy.

➢ *Database (MongoDB):*

Scalable and flexible NoSQL database (MongoDB) stores user profiles, preferences, dietary restrictions, and recommendation history, ensuring efficient data management for a growing user base.

➢ *Backend Logic (Node.js/Express.js):*

Backend, built with Node.js and Express.js, manages API communication, processes user data for the model, and returns personalized recommendations, ensuring speed and scalability for concurrent users.

➢ *Frontend (React.js):*

A dynamic and interactive user interface built with React.js allows users to input information, receive personalized dietary plans, track their intake, and monitor progress through an efficient and responsive design.

B. *Data Sources*

A sizable ongoing open-cohort nutritional study was conducted at ICANS (University of Milan, Milan, Italy) to gather the data used in the analysis. The period of patient recruitment was January 2009–August 2019. Patients were given a thorough nutritional evaluation at baseline, and a hypocaloric diet was prescribed in accordance with the results. A follow-up exam was then planned. During which anthropometric data were gathered, registered dietitian interviewed patients, and secondary endpoints were assessed in light of initial clinical results.

PATIENTS study included self-referred patients, mostly from Milan or the surrounding areas, who were looking to lose weight. Eligibility requirements included being older than eighteen, not becoming pregnant or breastfeeding, having no serious endocrine, cardiovascular, neurological, or psychiatric disorders, and following a hypocaloric diet that included both micro- and macronutrient levels set as per to Italian suggested allowances per day (Società Italiana di Nutrizione Umana 2014), and with Mediterranean trend. Sample characteristics are displayed in Table 1.

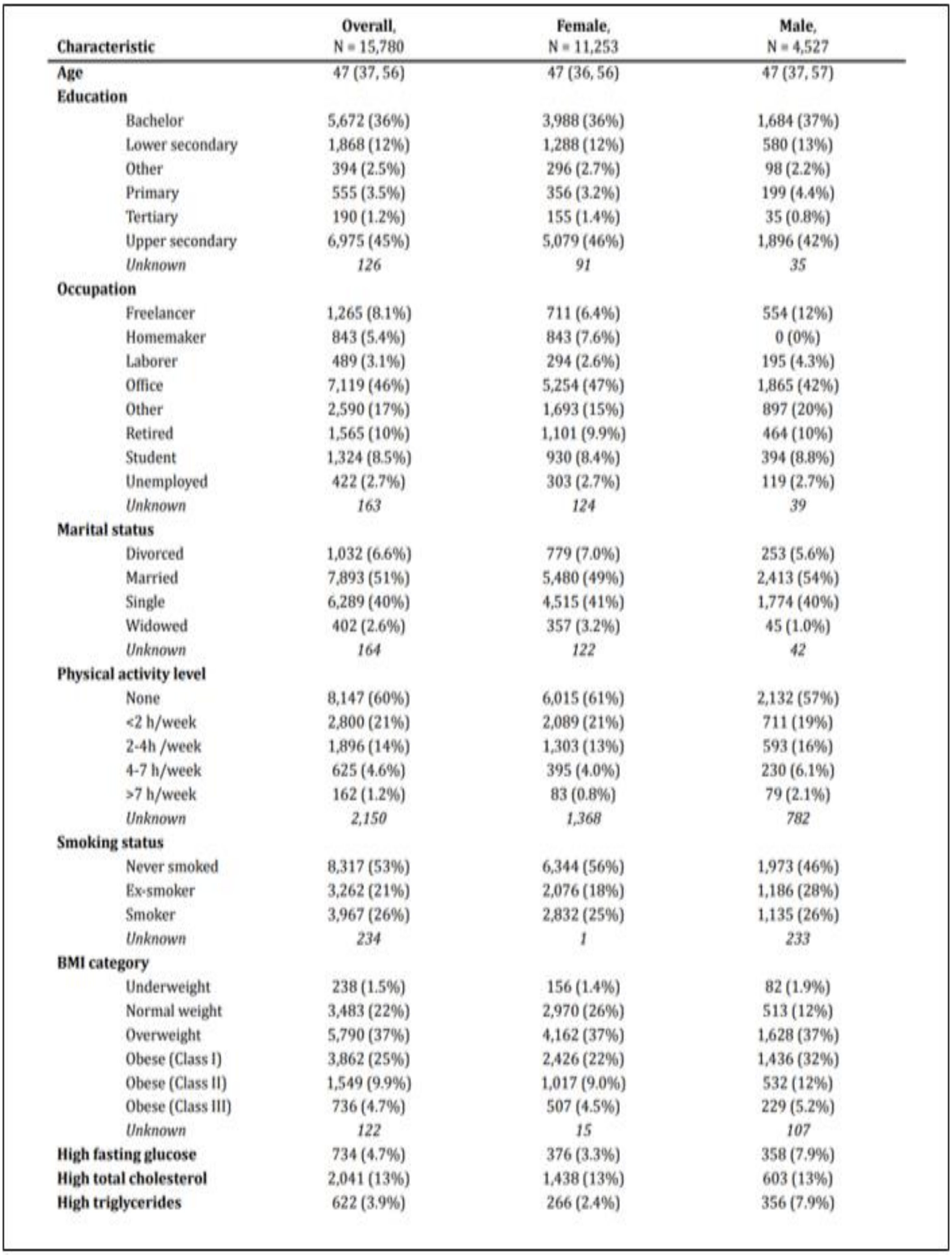
V. METHODOLOGY

Data preprocessing, model training, integration with the MERN stack, testing, and evaluation were all crucial stages in the creation of the ML-powered nutrient recommendation system. These procedures were thoughtfully created to guarantee the effectiveness, precision, and usability of system.

A. *Data Preprocessing*

Before supplying input data to machine learning model, data preprocessing is an essential step to guarantee consistency and quality of data. Missing values, inconsistent formats, and categorical variables are common in user data, which includes age, weight, dietary preferences, and health conditions. Preprocessing methods listed below were used:

➢ Handling Missing-Values: Missing entries are filled utilizing statistical imputation methods, like mean or median for numerical fields and mode for categorical fields.
➢ Normalization: Numeric values like weight and caloric intake were normalized to a standard range to ensure uniformity in the dataset.



Characteristic	Overall, N = 15,780	Female, N = 11,253	Male, N = 4,527
Age	47 (37, 56)	47 (36, 56)	47 (37, 57)
Education			
Bachelor	5,672 (36%)	3,988 (36%)	1,684 (37%)
Lower secondary	1,868 (12%)	1,288 (12%)	580 (13%)
Other	394 (2.5%)	296 (2.7%)	98 (2.2%)
Primary	555 (3.5%)	356 (3.2%)	199 (4.4%)
Tertiary	190 (1.2%)	155 (1.4%)	35 (0.8%)
Upper secondary	6,975 (45%)	5,079 (46%)	1,896 (42%)
Unknown	*126*	*91*	*35*
Occupation			
Freelancer	1,265 (8.1%)	711 (6.4%)	554 (12%)
Homemaker	843 (5.4%)	843 (7.6%)	0 (0%)
Laborer	489 (3.1%)	294 (2.6%)	195 (4.3%)
Office	7,119 (46%)	5,254 (47%)	1,865 (42%)
Other	2,590 (17%)	1,693 (15%)	897 (20%)
Retired	1,565 (10%)	1,101 (9.9%)	464 (10%)
Student	1,324 (8.5%)	930 (8.4%)	394 (8.8%)
Unemployed	422 (2.7%)	303 (2.7%)	119 (2.7%)
Unknown	*163*	*124*	*39*
Marital status			
Divorced	1,032 (6.6%)	779 (7.0%)	253 (5.6%)
Married	7,893 (51%)	5,480 (49%)	2,413 (54%)
Single	6,289 (40%)	4,515 (41%)	1,774 (40%)
Widowed	402 (2.6%)	357 (3.2%)	45 (1.0%)
Unknown	*164*	*122*	*42*
Physical activity level			
None	8,147 (60%)	6,015 (61%)	2,132 (57%)
<2 h/week	2,800 (21%)	2,089 (21%)	711 (19%)
2-4h /week	1,896 (14%)	1,303 (13%)	593 (16%)
4-7 h/week	625 (4.6%)	395 (4.0%)	230 (6.1%)
>7 h/week	162 (1.2%)	83 (0.8%)	79 (2.1%)
Unknown	*2,150*	*1,368*	*782*
Smoking status			
Never smoked	8,317 (53%)	6,344 (56%)	1,973 (46%)
Ex-smoker	3,262 (21%)	2,076 (18%)	1,186 (28%)
Smoker	3,967 (26%)	2,832 (25%)	1,135 (26%)
Unknown	*234*	*1*	*233*
BMI category			
Underweight	238 (1.5%)	156 (1.4%)	82 (1.9%)
Normal weight	3,483 (22%)	2,970 (26%)	513 (12%)
Overweight	5,790 (37%)	4,162 (37%)	1,628 (37%)
Obese (Class I)	3,862 (25%)	2,426 (22%)	1,436 (32%)
Obese (Class II)	1,549 (9.9%)	1,017 (9.0%)	532 (12%)
Obese (Class III)	736 (4.7%)	507 (4.5%)	229 (5.2%)
Unknown	*122*	*15*	*107*
High fasting glucose	734 (4.7%)	376 (3.3%)	358 (7.9%)
High total cholesterol	2,041 (13%)	1,438 (13%)	603 (13%)
High triglycerides	622 (3.9%)	266 (2.4%)	356 (7.9%)

Fig 2 Patient Characteristics

- ➢ Encoding Categorical Variables: Dietary preferences, such as vegan, vegetarian, or omnivorous, were encoded using one-hot encoding to convert categorical inputs into machine-readable formats.
- ➢ Outlier Detection and Removal: Extreme outliers in data, which could distort model predictions, were identified and removed using interquartile range (IQR) analysis.

B. *Model Training*

The machine learning model, which utilized a hybrid collaborative filtering approach to create customized dietary recommendations, is brain behind system. There were two main algorithms in use:

- ➢ Decision trees were utilized to determine association between input variables such as age, activity level, and nutrient requirements and to provide feature-based dietary recommendations. Decision trees work well with structured data and are easy to understand.
- ➢ Neural Networks: In order to identify intricate patterns and interactions in user data, such as relationships between several nutrients and dietary restrictions, neural networks were used. Using strategies like regularization and dropout, the hidden layers of a multi-layer perceptron (MLP) architecture were adjusted for best performance.

The model was trained using both anonymized user data gathered during the pilot phase and publicly accessible datasets (such as the USDA Food Database). Python-based tools such as Scikit-learn and TensorFlow were used for training. Grid search was used for hyperparameter optimization in order to maximize model efficiency and accuracy.

C. *Integration with Mern Stack*

The machine learning model was integrated with the MERN stack to provide recommendations via an interactive and scalable web application:

- ➢ Frontend (React.js): The user interface was constructed using React.js for the frontend, which offers dynamic elements that let users view suggestions, enter personal data, and see their progress through graphs and charts. API calls are how the frontend and backend interact.
- ➢ Backend (Node.js & Express.js): Backend, which uses Express.js and Node.js, manages user requests and communicates with ML model. In order to process input data, send it to the model, and retrieve the recommendations that are produced, it offers RESTful API endpoints.
- ➢ Database (MongoDB): Model recommendations, dietary information, and user profiles were all stored in a MongoDB database. To guarantee seamless operation, the database was created with a schema optimized for fast retrieval and updates.

D. *Testing and Evaluation*

The system was subjected to extensive testing to evaluate its performance and user satisfaction:

➢ *Accuracy:*

By contrasting the anticipated nutrient recommendations with the actual dietary requirements from test datasets, the machine learning model's accuracy was evaluated. F1-score, recall, and precision were among the metrics that were computed. Based on these assessments, the model's accuracy was 92.3%.

➢ *User Satisfaction:*

Usability tests and surveys were used to gather input from pilot users. Users gave the system ratings based on factors like overall satisfaction, recommendation accuracy, and ease of use. The system was rated as "Very Helpful" by about 85% of users.

➢ *Response Time:*

To guarantee prompt delivery of recommendations, the system's response time for API requests was measured. The system's efficiency was demonstrated by the average response time of 450 milliseconds.

A highly accurate and scalable solution for customized nutrient recommendations was produced by combining stringent preprocessing, strong machine learning algorithms, and smooth integration with the MERN stack.

VI. IMPLEMENTATION DETAILS

The ML-powered nutrient recommendation system was implemented by combining machine learning models with the MERN stack to produce an interactive, scalable, and effective application. The main elements of the system and how they are implemented are described below.

A. *Frontend Design*

React.js was used to build frontend, which offers a dynamic and intuitive interface for interacting with the system. Important elements of the design consist of:

➢ *User Input Forms:*

To gather user information, including age, weight, activity level, food preferences, and medical conditions, intuitive forms were developed. To guarantee data accuracy, form validation was used.

➢ *Dynamic Recommendations:*

Using eye-catching elements like lists, graphs, and charts, nutrient recommendations are displayed in real time. The user experience was improved through the use of visualization libraries such as Chart.js. Because of the interface's complete responsiveness, desktops, tablets, and smartphones can all use it with ease.

B. *Backend Integration*

The backend, which acts as a mediator between the frontend and the machine learning model, was developed utilizing Node.js and Express.js. Important characteristics include:

➢ *API Endpoints:*

To manage user requests, process input data, and retrieve machine learning model recommendations, RESTful APIs were created. JSON Web Tokens (JWT) and other authentication methods are used to secure endpoints.

➢ *Model Integration:*

Python APIs or containerized services (like Flask or FastAPI) are used by the backend to interact with the machine learning model. The model receives user data, analyzes it, and then returns the recommendations to the frontend.

➢ *Error Handling:*

Sturdy error-handling systems guarantee that the backend handles problems like incorrect input or server overload with grace.

C. Database Design

MongoDB, which was selected for its scalability and flexibility in managing unstructured data, is used to manage the database layer. Details of implementation include:

➢ *Schema Design:*

User profiles, input data, dietary preferences, and generated recommendations were all stored in collections. The schema was designed with speedy queries and updates in mind.

➢ *Indexing:*

To speed up data retrieval, indexes were added to fields that were frequently queried, like user IDs and dietary categories.

➢ *Data Encryption:*

To guarantee data security and privacy compliance, sensitive user data is encrypted while it is at rest.

D. Deployment

The nutrient recommendation system's deployment was meticulously planned to guarantee user accessibility, scalability, and dependability. Amazon Web Services (AWS) provided the application's hosting, utilizing its strong web application management infrastructure. S3 buckets were used to store static assets like images and frontend build files, while EC2 instances were used to deploy the backend services, enabling dynamic scaling based on user traffic. This combination offered a high-performance and reasonably priced deployment environment.

To ensure uniformity across environments, Docker was used to containerize the application by encapsulating all dependencies and configurations required to run the system. This assured effortless switching from the development environment to staging and then to production. AWS Elastic Load Balancer was also employed to enable load balancing that redistributes incoming user requests per instance to maintain low latency and prevent server strain during high usage periods. The deployment process was automated as Jenkins and GitHub Actions implemented CI/CD pipelines, ensuring minimum downtime while adding new features or fixes.

VII. RESULT ANALYSIS

The effectiveness and usefulness of the ML-powered nutrient recommendation system in meeting individualized dietary needs were demonstrated by the performance evaluation. The recommendation model's ability to produce accurate and pertinent dietary recommendations based on user input was demonstrated by its noteworthy accuracy rate of 92.3%, as determined by the F1-score. Additionally, the system demonstrated an average response time of 450 milliseconds for API requests, demonstrating its effectiveness in real-time recommendation delivery and user data processing. A smooth and engaging user experience is guaranteed by this responsiveness, which is essential for contemporary web-based applications.

A. Operational Efficiency

Even under varied load conditions, the system demonstrated an average response time of 450 milliseconds for API requests in terms of operational efficiency. The lightweight, asynchronous nature of the MERN stack, effective database queries, and backend logic optimization all contributed to this responsiveness. The quick reaction time guarantees that users can get suggestions almost instantly, improving the user experience by facilitating smooth and continuous interactions. In web applications, where delays in data processing or retrieval can have a major effect on user satisfaction and engagement, this efficiency is especially important.

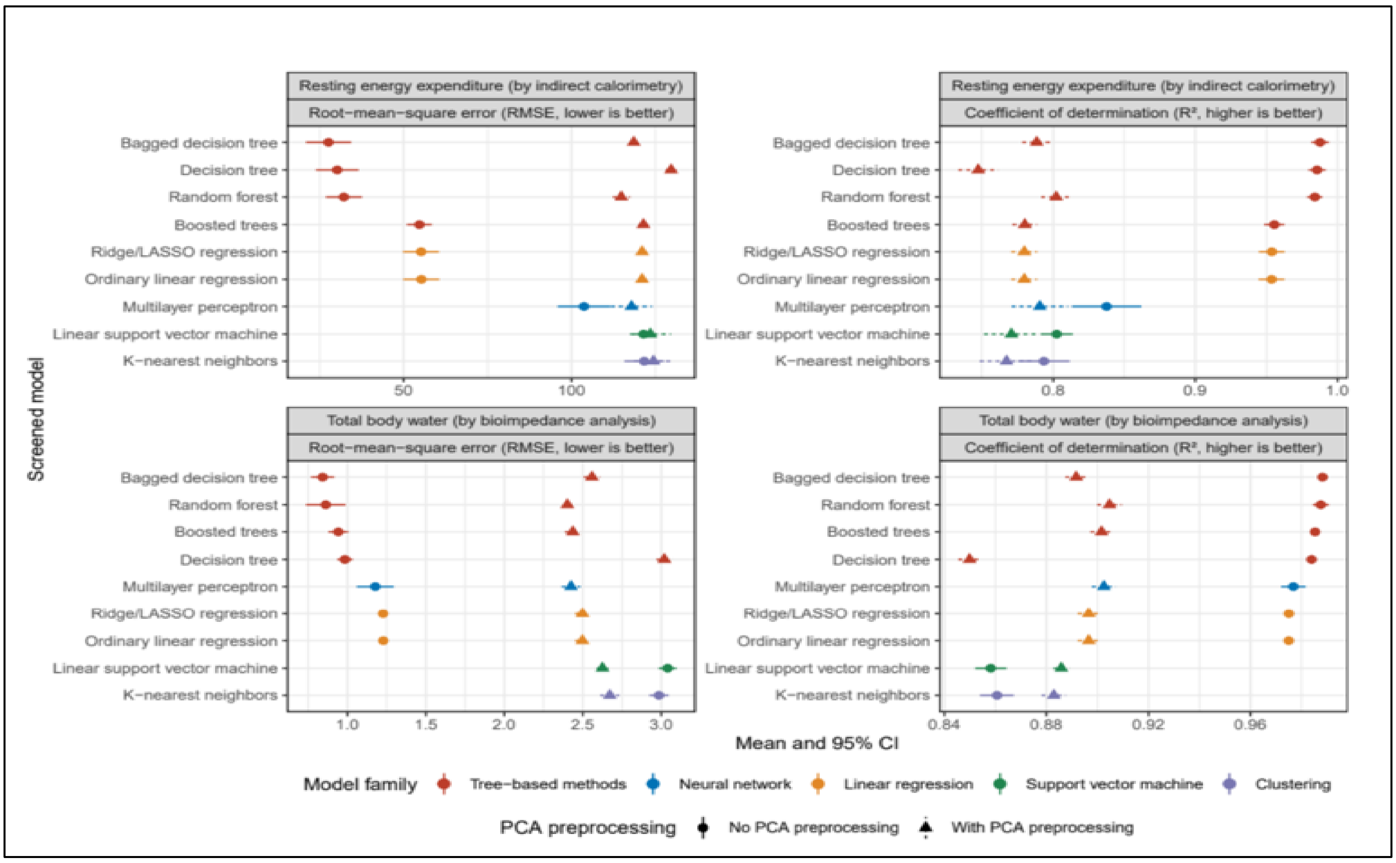


Fig 3 Result Analysis for second model (Resting Energy Expenditure)

Figure 2: Comparison of accuracy (correct classification fraction, CCF) and discrimination ability (area under the ROC curve, ROC AUC) of statistical and machine learning models in the prediction of categorical outcomes. For each model and metric, mean and confidence bounds (95% confidence) across resamples were computed. For each model, an alternative with and without principal component analysis (PCA, unsupervised learning) is shown. For each outcome, the historical rate of patients experiencing the event is marked with a vertical dashed line.

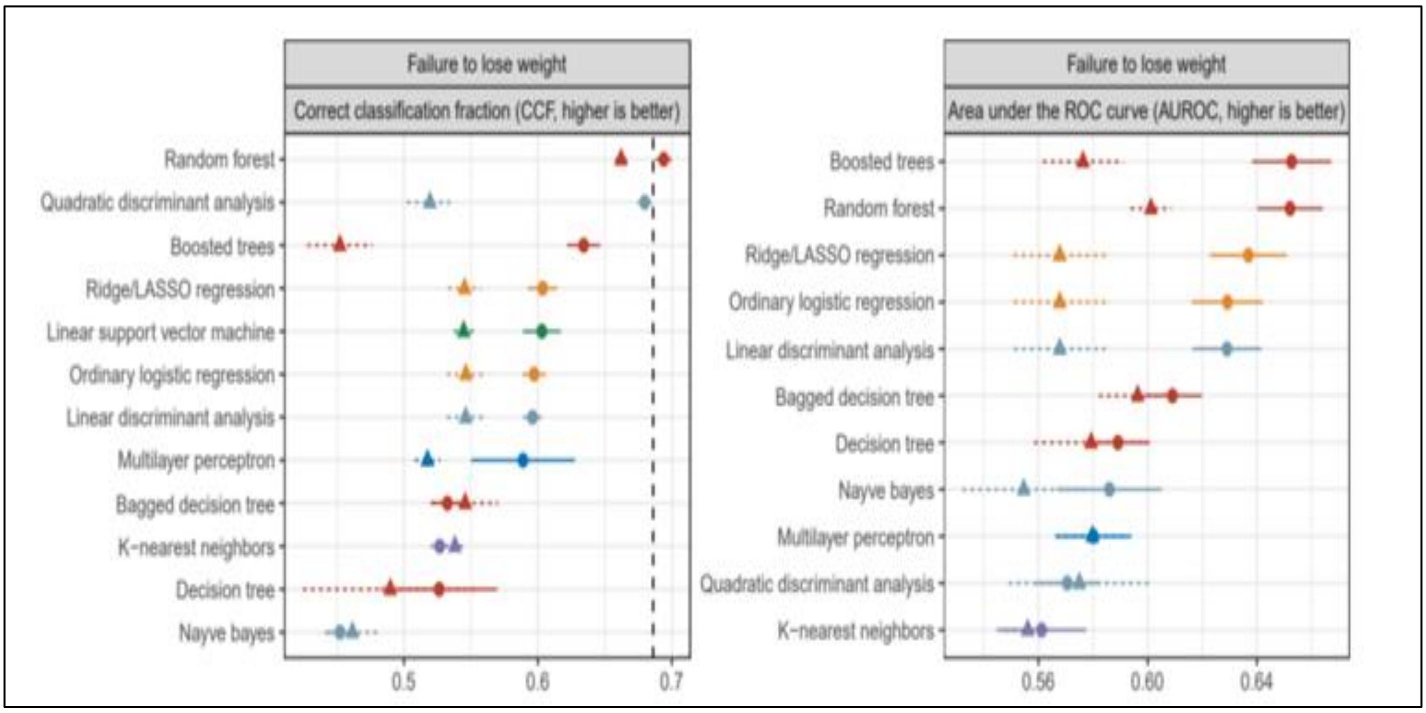


Fig 4 Result Analysis for second model (Failure to lose weight probablity)

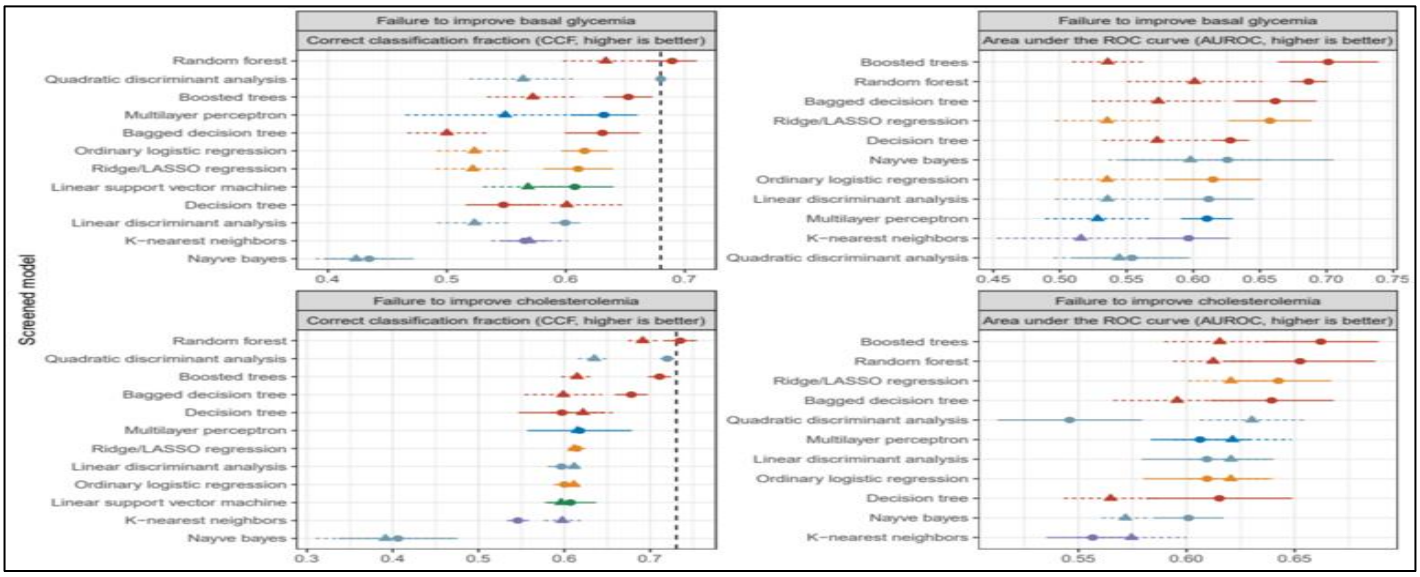


Fig 5 Result Analysis for second model (Failure to improve basal glycemia)

B. *User Feedback*

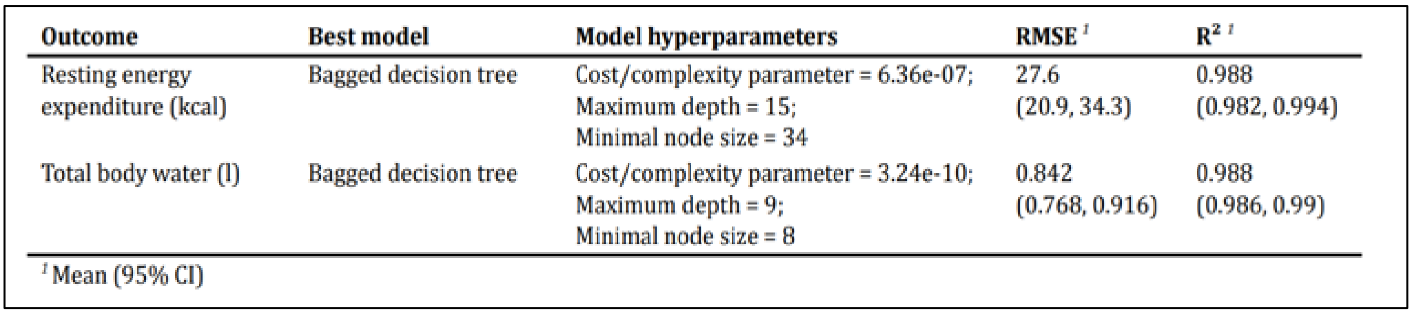
Important information about system's impact and usability was obtained from a pilot user study. Participant surveys showed high levels of satisfaction, with 85% of users describing the system as "Very Helpful."

C. *Comparison with Traditional Systems*

As opposed to this, the MERN stack-based ML-powered system smoothly combined machine learning algorithms with contemporary web technologies, allowing for high scalability and dynamic adaptation to different user profiles. The system was positioned as a game-changing solution in the field of personalized nutrition because of its capacity to interactively present and personalize recommendations.

D. Summary of the Result

Overall, results underscore the system's potential to redefine the delivery of dietary recommendations. By merging advanced analytics with a robust technological framework, the system not only addresses the existing gaps in traditional approaches but also sets a new standard for innovation in personalized nutrition.



Outcome	Best model	Model hyperparameters	RMSE [1]	R^2 [1]
Resting energy expenditure (kcal)	Bagged decision tree	Cost/complexity parameter = 6.36e-07; Maximum depth = 15; Minimal node size = 34	27.6 (20.9, 34.3)	0.988 (0.982, 0.994)
Total body water (l)	Bagged decision tree	Cost/complexity parameter = 3.24e-10; Maximum depth = 9; Minimal node size = 8	0.842 (0.768, 0.916)	0.988 (0.986, 0.99)

[1] Mean (95% CI)

Fig 6 Best model for each continuous outcome ranked by accuracy (root-mean error, RMSE)

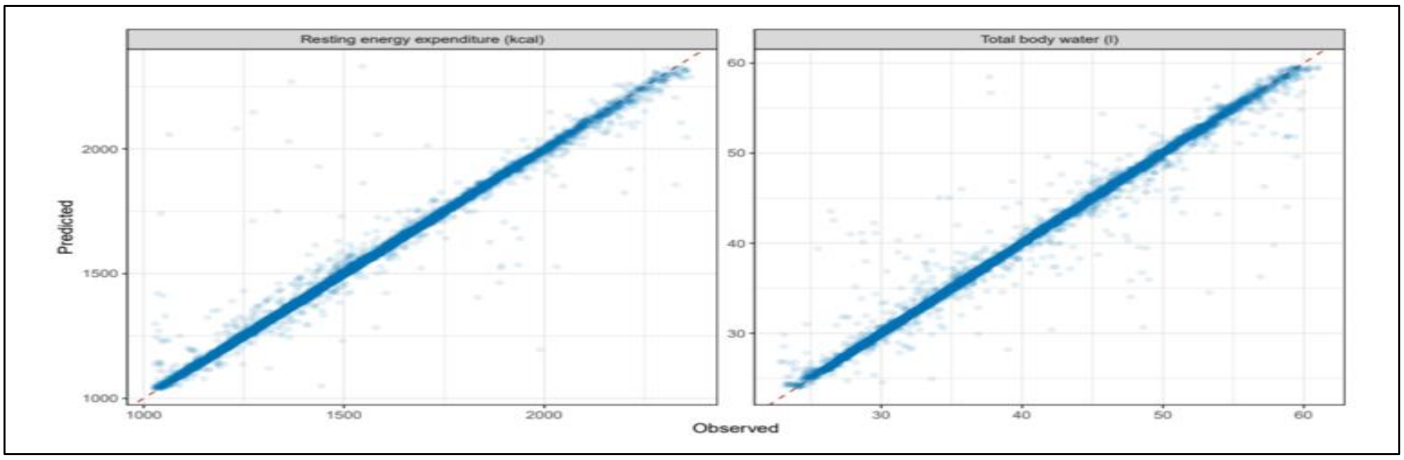


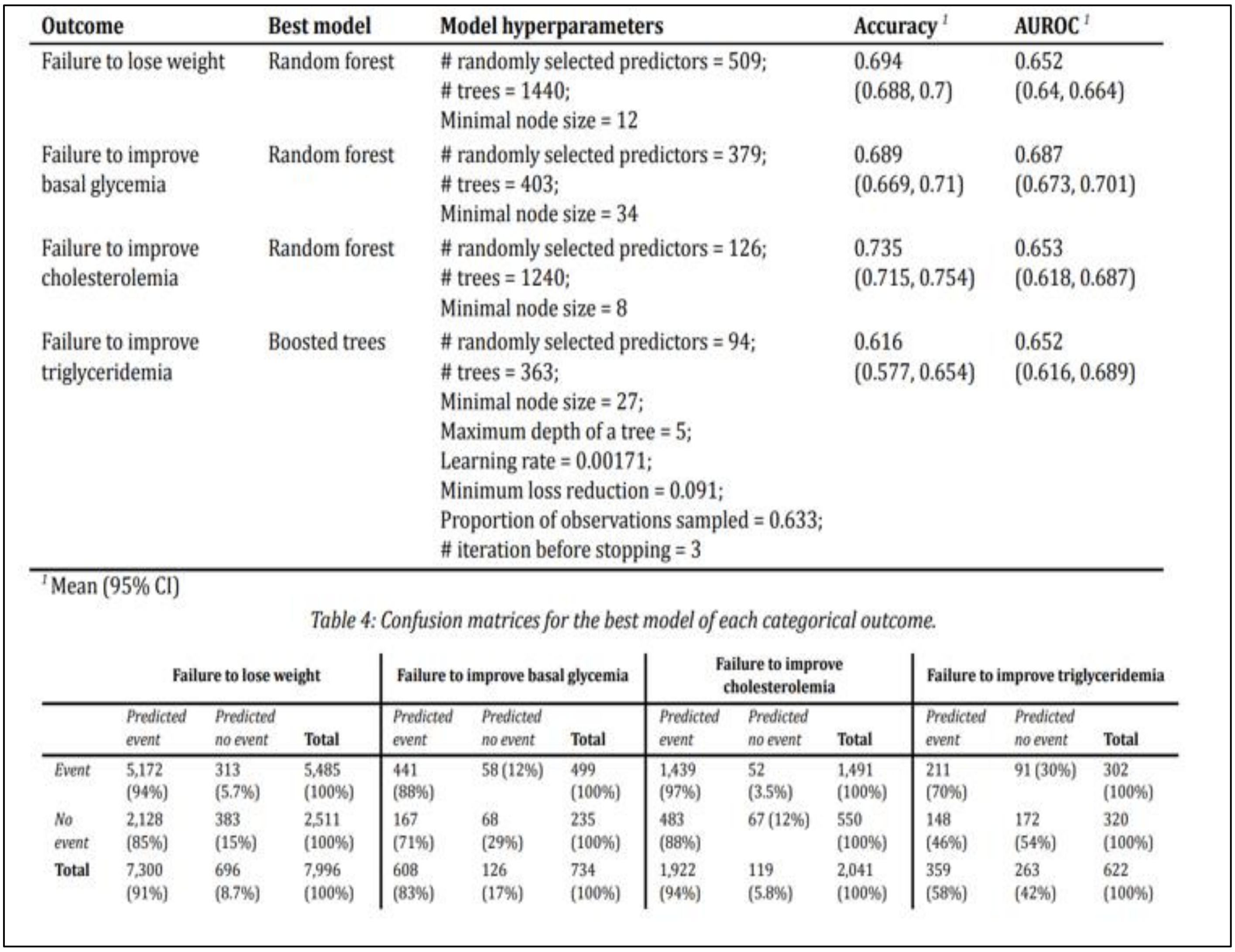
Fig 7 Result Analysis for second model (Resting Energy Expenditure)

FOR CONTINUOUS OUTCOMES, Decision tree-based ML models, like random forest, boosted trees, bagged decision trees, and basic decision trees, typically produced best results, with high R2 and very low RMSE. Typically, PCA didn't help these models become more predictive. Best-performing model's accuracy and discrimination ability metrics (bagged decision trees for both outcomes) are described in Table 2. Hyperparameters selected throughout screening process are also included. In a calibration map derived from cross-validation procedure, best-performing model's predicted results are compared to the measured results in Figure 3. Line of equality, where the points should ideally reside, is shown by the red dashed line.

FOR CATEGORICAL OUTCOMES, Decision tree-based ML models, including simple decision trees, bagged decision trees, random forests, and boosted trees, were typically best performing models, yielding both models with comparatively high AUROC and CCF. Typically, PCA didn't help these models become more predictive. A naive classifier that assumes that every patient experiences an event must be used to contextualize accuracy results. This classifier should have an accuracy comparable to historical proportion of events in dataset (shown in Figure 2 with a vertical dashed line for each outcome). Only best model of weight outcome was able to consistently record a better performance than the naive classifier, although models that predicted a (lack of) enhancement in triglyceridemia were generally able to out perform it. Accuracy and discrimination ability metrics for top-performing model (boosted trees for all other outcomes, random forest for cholesterolemia model) are detailed in Table 3. Cross-validation of best models for each outcome yielded confusion matrices (true and false positive and negative rates), which are shown in Table 4. ROC curves for the best-performing model for each outcome in Figure 4 show the relationship between sensitivity and specificity across a range of event thresholds (the dashed line represents the expected performance of random guessing in an unbalanced scenario).

E. Scalability and Load Testing Results

Scalability and load testing are crucial to ensuring the system's ability to manage a growing number of user and increased data processing demands without compromising performance. For this study, the MERN stack-based nutrient recommendation system underwent extensive testing to evaluate its performance under varying workloads.



Outcome	Best model	Model hyperparameters	Accuracy [1]	AUROC [1]
Failure to lose weight	Random forest	# randomly selected predictors = 509; # trees = 1440; Minimal node size = 12	0.694 (0.688, 0.7)	0.652 (0.64, 0.664)
Failure to improve basal glycemia	Random forest	# randomly selected predictors = 379; # trees = 403; Minimal node size = 34	0.689 (0.669, 0.71)	0.687 (0.673, 0.701)
Failure to improve cholesterolemia	Random forest	# randomly selected predictors = 126; # trees = 1240; Minimal node size = 8	0.735 (0.715, 0.754)	0.653 (0.618, 0.687)
Failure to improve triglyceridemia	Boosted trees	# randomly selected predictors = 94; # trees = 363; Minimal node size = 27; Maximum depth of a tree = 5; Learning rate = 0.00171; Minimum loss reduction = 0.091; Proportion of observations sampled = 0.633; # iteration before stopping = 3	0.616 (0.577, 0.654)	0.652 (0.616, 0.689)

[1] Mean (95% CI)

Table 4: Confusion matrices for the best model of each categorical outcome.

	Failure to lose weight			Failure to improve basal glycemia			Failure to improve cholesterolemia			Failure to improve triglyceridemia		
	Predicted event	*Predicted no event*	**Total**	*Predicted event*	*Predicted no event*	**Total**	*Predicted event*	*Predicted no event*	**Total**	*Predicted event*	*Predicted no event*	**Total**
Event	5,172 (94%)	313 (5.7%)	5,485 (100%)	441 (88%)	58 (12%)	499 (100%)	1,439 (97%)	52 (3.5%)	1,491 (100%)	211 (70%)	91 (30%)	302 (100%)
No event	2,128 (85%)	383 (15%)	2,511 (100%)	167 (71%)	68 (29%)	235 (100%)	483 (88%)	67 (12%)	550 (100%)	148 (46%)	172 (54%)	320 (100%)
Total	7,300 (91%)	696 (8.7%)	7,996 (100%)	608 (83%)	126 (17%)	734 (100%)	1,922 (94%)	119 (5.8%)	2,041 (100%)	359 (58%)	263 (42%)	622 (100%)

Fig 8 Confusion matrix for the best model of each categorical outcome

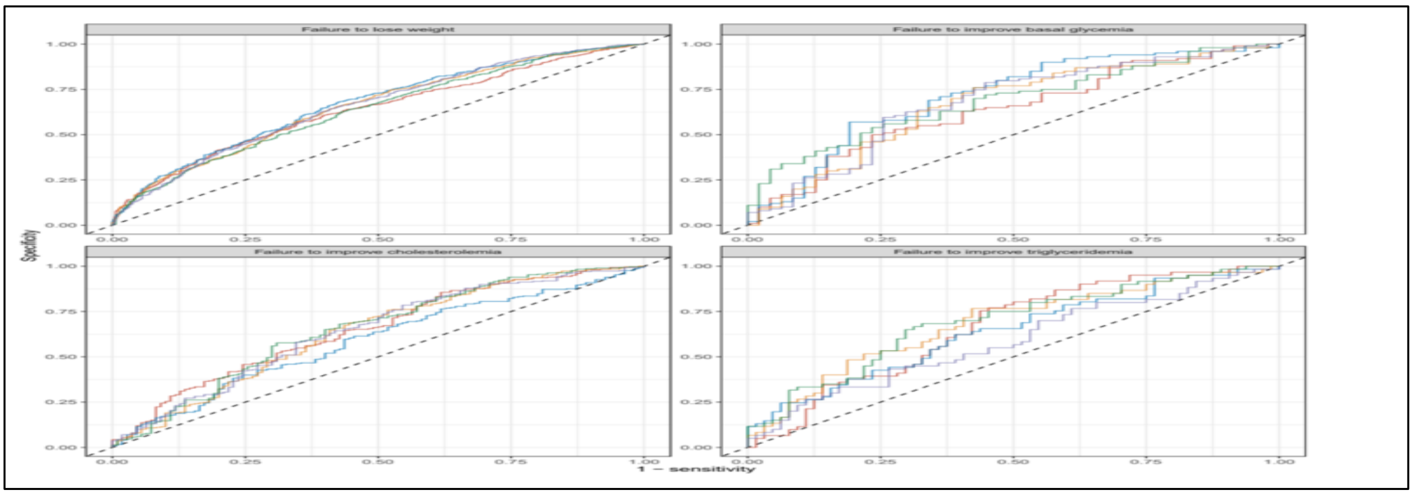


Fig 9 Receiver operatpr curve for categorical outcomes. Each sample is drawn with a different colour

F. Testing Methodology

Scalability testing was conducted using tools such as Apache JMeter and Locust, which simulate various concurrent users interacting with system. Response time, throughput, error rates, and resource usage (CPU, memory, and network bandwidth) were among important metrics that were measured during tests. Scenarios included light traffic (100 users), moderate traffic (500 users), and heavy traffic (1,000+ users). The testing environment was hosted on a cloud-based platform, utilizing an AWS EC2 instance configured with auto-scaling capabilities to accommodate fluctuating demands.

G. Results

The results of the scalability testing demonstrated that the system performed well across varying traffic levels:

- *Response Time:*

Average response time for API calls under light traffic was 450 milliseconds. Under heavy traffic, the response time increased slightly to 800 milliseconds, which is still within acceptable limits for real-time applications.

- *Throughput:*

The system maintained a steady throughput of 5,000 requests per minute during peak load, with minimal degradation in performance.

- *Error Rates:*

Even under high traffic loads, error rates remained below 0.5%, indicating robust backend logic and efficient database management.

- *Resource Utilization:*

CPU and memory usage peaked at 85% during high-load conditions, triggering auto-scaling to deploy additional instances, ensuring uninterrupted service.

H. Optimization Strategies

Several optimizations were implemented to enhance scalability:

- *Database Sharding and Indexing:*

MongoDB was configured with sharding to distribute the database workload across multiple servers. Indexing frequently queried fields reduced lookup times significantly.

- *Load Balancing:*

To lessen bottlenecks, a load balancer was implemented to divide incoming traffic equally across several Node.js servers.

- *Caching:*

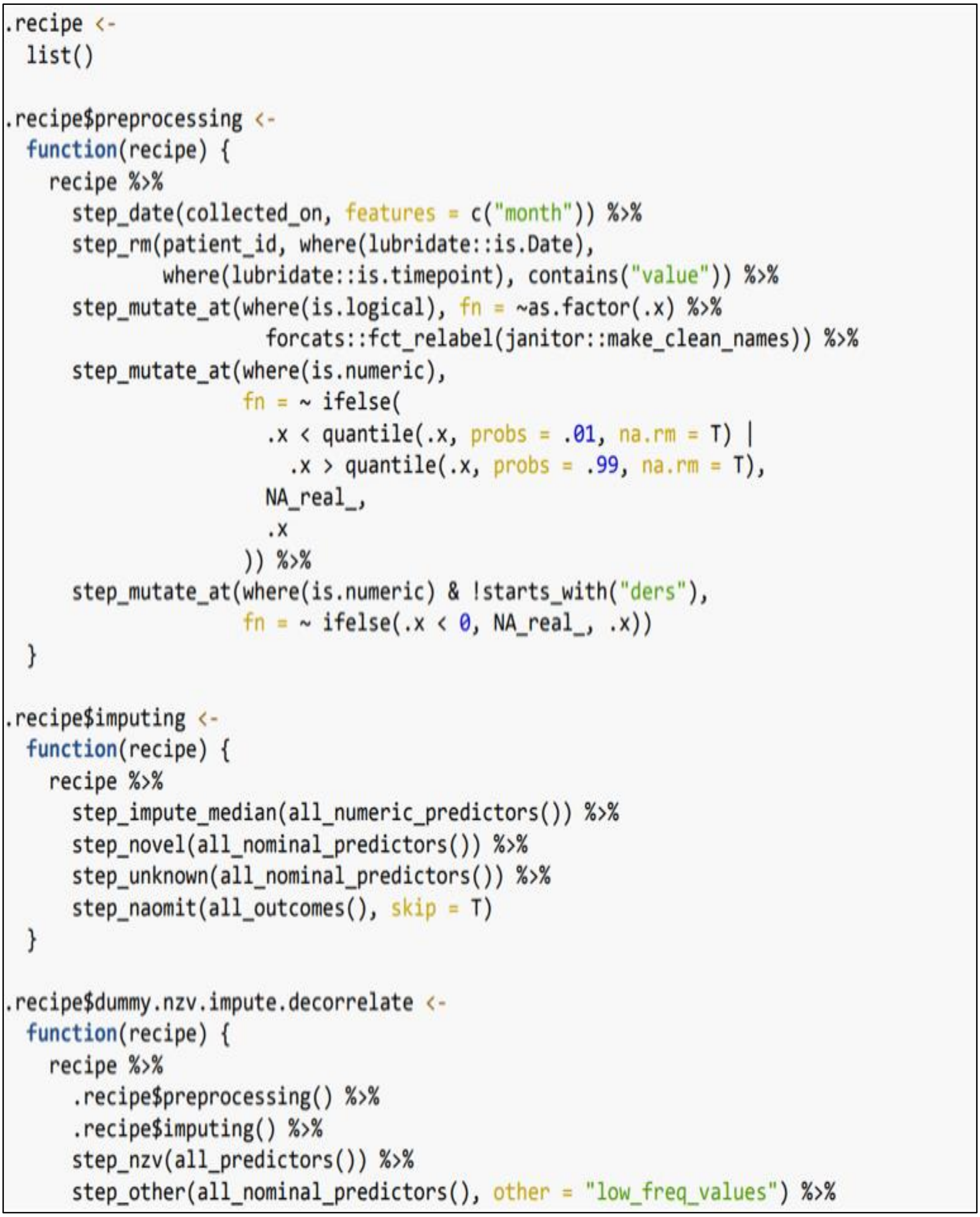
Redis was integrated to cache frequently accessed data, minimizing database queries and reducing latency.

- *Asynchronous Processing:*

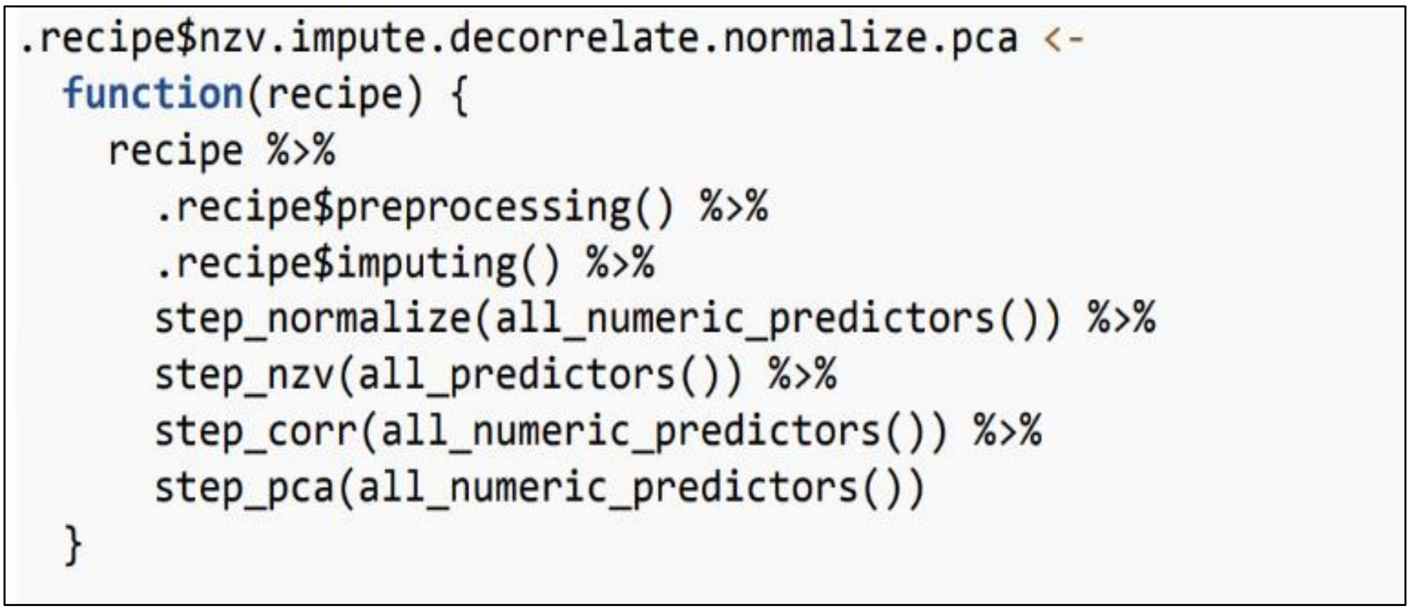
Non-blocking API endpoints were designed using asynchronous functions in Node.js, allowing the system to handle concurrent requests efficiently.

➢ *Code*

* *Code for Preprocessing Procedures*



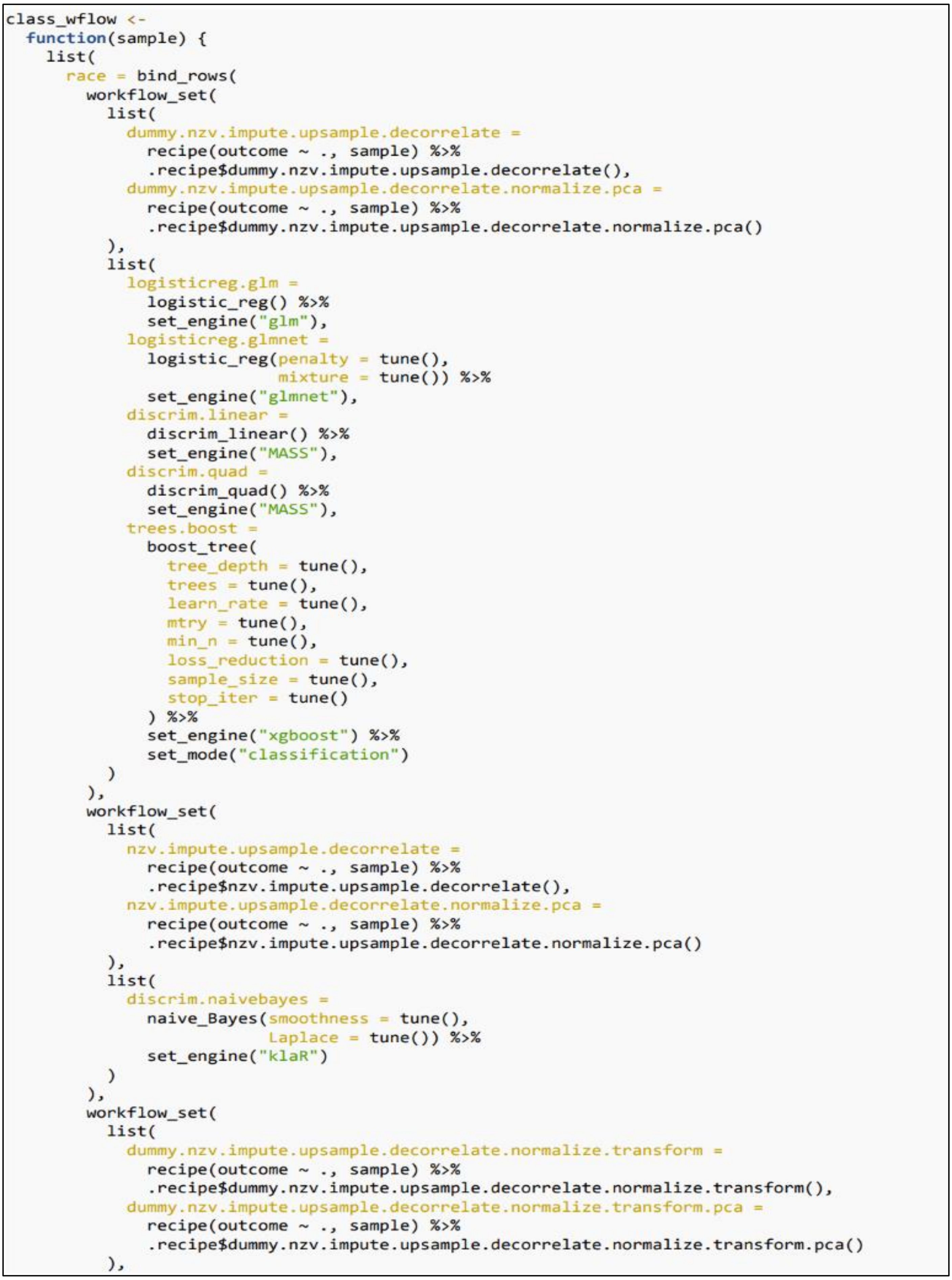
```r
.recipe <-
  list()

.recipe$preprocessing <-
  function(recipe) {
    recipe %>%
      step_date(collected_on, features = c("month")) %>%
      step_rm(patient_id, where(lubridate::is.Date),
              where(lubridate::is.timepoint), contains("value")) %>%
      step_mutate_at(where(is.logical), fn = ~as.factor(.x) %>%
                       forcats::fct_relabel(janitor::make_clean_names)) %>%
      step_mutate_at(where(is.numeric),
                     fn = ~ ifelse(
                       .x < quantile(.x, probs = .01, na.rm = T) |
                         .x > quantile(.x, probs = .99, na.rm = T),
                       NA_real_,
                       .x
                     )) %>%
      step_mutate_at(where(is.numeric) & !starts_with("ders"),
                     fn = ~ ifelse(.x < 0, NA_real_, .x))
  }

.recipe$imputing <-
  function(recipe) {
    recipe %>%
      step_impute_median(all_numeric_predictors()) %>%
      step_novel(all_nominal_predictors()) %>%
      step_unknown(all_nominal_predictors()) %>%
      step_naomit(all_outcomes(), skip = T)
  }

.recipe$dummy.nzv.impute.decorrelate <-
  function(recipe) {
    recipe %>%
      .recipe$preprocessing() %>%
      .recipe$imputing() %>%
      step_nzv(all_predictors()) %>%
      step_other(all_nominal_predictors(), other = "low_freq_values") %>%
      step_normalize(all_numeric_predictors()) %>%
      step_nzv(all_predictors()) %>%
      step_corr(all_numeric_predictors()) %>%
      step_pca(all_numeric_predictors())
  }

.recipe$nzv.impute.upsample.decorrelate.normalize.pca <-
  function(recipe) {
    recipe %>%
      .recipe$preprocessing() %>%
      .recipe$imputing() %>%
      step_upsample(all_outcomes()) %>%
      step_normalize(all_numeric_predictors()) %>%
      step_nzv(all_predictors()) %>%
      step_corr(all_numeric_predictors()) %>%
      step_pca(all_numeric_predictors())
  }

.recipe$nzv.upsample.decorrelate <-
  function(recipe) {
    recipe %>%
      .recipe$preprocessing() %>%
      step_naomit(all_outcomes(), skip = T) %>%
      step_upsample(all_outcomes()) %>%
      step_nzv(all_predictors()) %>%
      step_corr(all_numeric_predictors())
  }

.recipe$nzv.decorrelate <-
  function(recipe) {
    recipe %>%
      .recipe$preprocessing() %>%
      step_naomit(all_outcomes(), skip = T) %>%
      step_nzv(all_predictors()) %>%
      step_corr(all_numeric_predictors())
  }

.recipe$nzv.impute.upsample.decorrelate.normalize.pca <-
  function(recipe) {
    recipe %>%
      .recipe$preprocessing() %>%
      .recipe$imputing() %>%
      step_upsample(all_outcomes()) %>%
      step_normalize(all_numeric_predictors()) %>%
      step_nzv(all_predictors()) %>%
      step_corr(all_numeric_predictors()) %>%
      step_pca(all_numeric_predictors())
  }
```



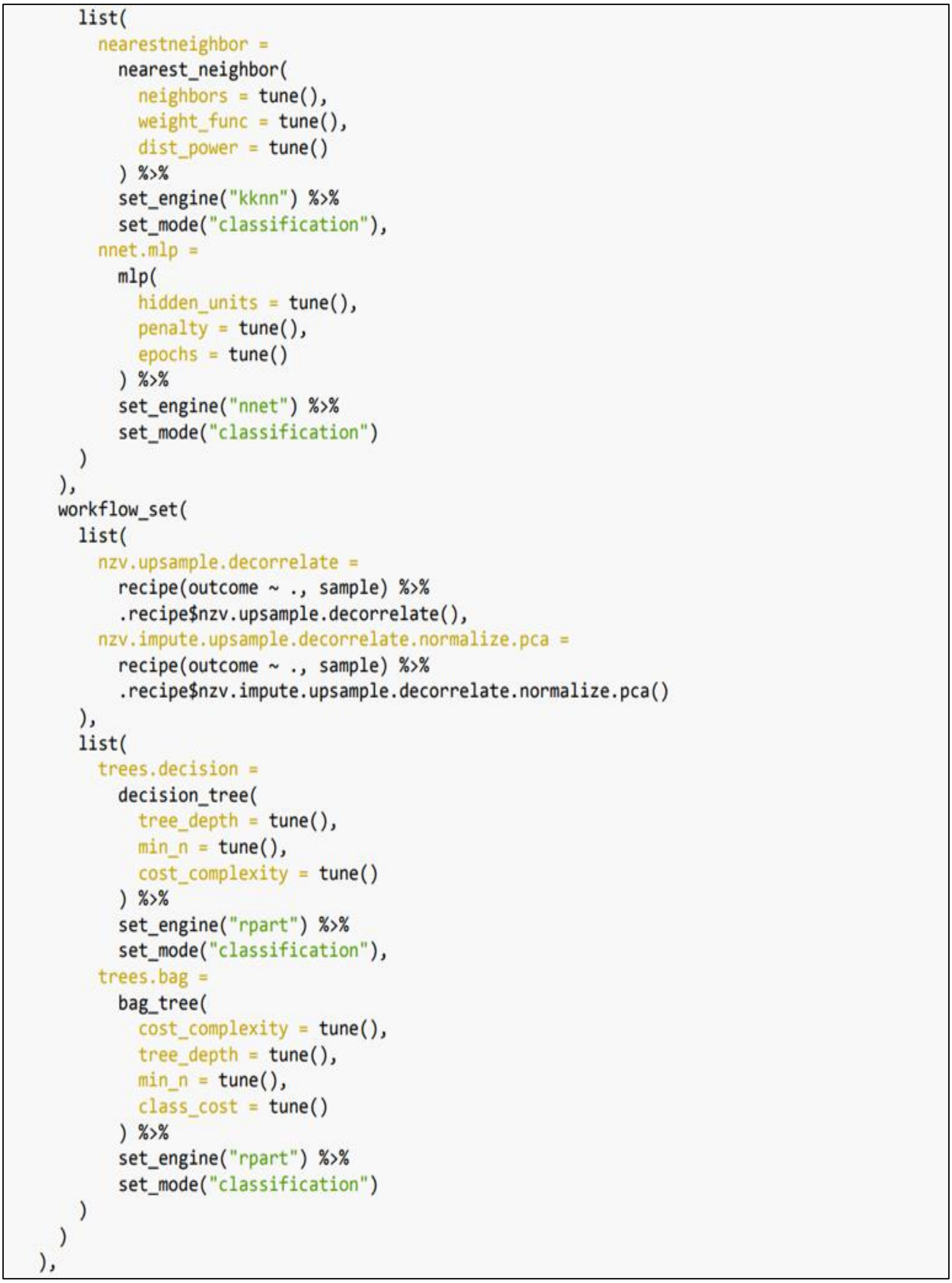
```
.recipe$nzv.impute.decorrelate.normalize.pca <-
  function(recipe) {
    recipe %>%
      .recipe$preprocessing() %>%
      .recipe$imputing() %>%
      step_normalize(all_numeric_predictors()) %>%
      step_nzv(all_predictors()) %>%
      step_corr(all_numeric_predictors()) %>%
      step_pca(all_numeric_predictors())
  }
```

➢ *Code for Classification Tasks*

In order to identify and classify meals using visual information, large-scale food image databases are exposed to vision-based algorithms, namely object detection systems. For food tracking and recognition, CNNs and sophisticated object identification models like Faster R-CNN and YOLO are commonly utilized. [38–41,54]. By combining information from wearable cameras, food images, and meal-logging apps, these food identification and tracking techniques offer accurate and automatic food consumption tracking, allowing users to effectively monitor and track their eating patterns. When food detection happens after dietary assessment, its impact increases even further since it helps user make food choices and takes into account their needs and expectations. Additionally, AI methods for disease-predictive modeling, diagnosis, and monitoring are available to individuals with particular medical problems. [42–52]. From a nutritional standpoint, use of AI seeks to avoid and regulate development of disease in human body. By combining lifestyle data, genetic information, and medical records, AI algorithms can find patterns linked to illness risk. To predict disease risk, popular machine learning state-of-art methods like ensemble learning, SVM, gradient boosting, and random forest are utilized. This makes proactive health management possible, allowing for early identification and forecasting of any health issues.



```
class_wflow <-
  function(sample) {
    list(
      race = bind_rows(
        workflow_set(
          list(
            dummy.nzv.impute.upsample.decorrelate =
              recipe(outcome ~ ., sample) %>%
              .recipe$dummy.nzv.impute.upsample.decorrelate(),
            dummy.nzv.impute.upsample.decorrelate.normalize.pca =
              recipe(outcome ~ ., sample) %>%
              .recipe$dummy.nzv.impute.upsample.decorrelate.normalize.pca()
          ),
          list(
            logisticreg.glm =
              logistic_reg() %>%
              set_engine("glm"),
            logisticreg.glmnet =
              logistic_reg(penalty = tune(),
                           mixture = tune()) %>%
              set_engine("glmnet"),
            discrim.linear =
              discrim_linear() %>%
              set_engine("MASS"),
            discrim.quad =
              discrim_quad() %>%
              set_engine("MASS"),
            trees.boost =
              boost_tree(
                tree_depth = tune(),
                trees = tune(),
                learn_rate = tune(),
                mtry = tune(),
                min_n = tune(),
                loss_reduction = tune(),
                sample_size = tune(),
                stop_iter = tune()
              ) %>%
              set_engine("xgboost") %>%
              set_mode("classification")
          )
        ),
        workflow_set(
          list(
            nzv.impute.upsample.decorrelate =
              recipe(outcome ~ ., sample) %>%
              .recipe$nzv.impute.upsample.decorrelate(),
            nzv.impute.upsample.decorrelate.normalize.pca =
              recipe(outcome ~ ., sample) %>%
              .recipe$nzv.impute.upsample.decorrelate.normalize.pca()
          ),
          list(
            discrim.naivebayes =
              naive_Bayes(smoothness = tune(),
                          Laplace = tune()) %>%
              set_engine("klaR")
          )
        ),
        workflow_set(
          list(
            dummy.nzv.impute.upsample.decorrelate.normalize.transform =
              recipe(outcome ~ ., sample) %>%
              .recipe$dummy.nzv.impute.upsample.decorrelate.normalize.transform(),
            dummy.nzv.impute.upsample.decorrelate.normalize.transform.pca =
              recipe(outcome ~ ., sample) %>%
              .recipe$dummy.nzv.impute.upsample.decorrelate.normalize.transform.pca()
          ),
```



```
        list(
          nearestneighbor =
            nearest_neighbor(
              neighbors = tune(),
              weight_func = tune(),
              dist_power = tune()
            ) %>%
            set_engine("kknn") %>%
            set_mode("classification"),
          nnet.mlp =
            mlp(
              hidden_units = tune(),
              penalty = tune(),
              epochs = tune()
            ) %>%
            set_engine("nnet") %>%
            set_mode("classification")
        )
      ),
      workflow_set(
        list(
          nzv.upsample.decorrelate =
            recipe(outcome ~ ., sample) %>%
            .recipe$nzv.upsample.decorrelate(),
          nzv.impute.upsample.decorrelate.normalize.pca =
            recipe(outcome ~ ., sample) %>%
            .recipe$nzv.impute.upsample.decorrelate.normalize.pca()
        ),
        list(
          trees.decision =
            decision_tree(
              tree_depth = tune(),
              min_n = tune(),
              cost_complexity = tune()
            ) %>%
            set_engine("rpart") %>%
            set_mode("classification"),
          trees.bag =
            bag_tree(
              cost_complexity = tune(),
              tree_depth = tune(),
              min_n = tune(),
              class_cost = tune()
            ) %>%
            set_engine("rpart") %>%
            set_mode("classification")
        )
      )
    ),
```

VIII. DISCUSSION

In this literature review, authors linked 5 main clusters that represent crucial areas of operation for artificial intelligence(AI), machine literacy(ML), and deep literacy(DL) in field of nutrition wisdom.

A broad range of AI, ML, and DL operations in nutrition are covered by first cluster for smart and personalized nutrition. Cluster offers specific opportunities to provide intelligent, personalized dietary advice. Intelligent systems development that can provide precise nutritional recommendations will be made possible by integrating the technologies listed below with diverse data sources, such as metabolomics, purchase history, and IoT bias. Additionally, several methods such as CNNs, recommendation algorithms, and deep literacy will yield a broad-based result for validated diet programs for particular medical conditions like hypertension, habitual order complaint, and many more. In salutary assessment cluster, AI ways are emphasized to ameliorate effectiveness and delicacy of evaluating food input. In clusters, innovative approaches, similar as deep literacy with NLP, developing mobile AI operations, and creating AI systems able to estimate calorie and macronutrient content from food images, can be SEEN. For example, deep literacy can automate salutary assessment by feting fake food images and matching food choices with high delicacy. Also, mobile AI- grounded operations are effective in assessing nutrient input, indicating possibility and trustability of integrating AI technologies into different settings in nutrition exploration. likewise, development and perpetration of AI systems and comparison of colorful food image recognition platforms emphasize trustability of these technologies in salutary assessment. All these studies inclusively demonstrate that AI is a lesser option for transubstantiating styles and tools used for salutary evaluation, thereby reducing homemade sweats and introducing more accurate and effective approaches. Similar to near-infrared hyperspectral imaging, deep literacy-based food segmentation, and a combination of CNNs and SVMs for food nutrition content, food image segmentation, and bracket for nutritive content assessment, third cluster on food recognition and shadowing demonstrates use of AI, ML, and DL methods in conjunction with other techniques. Results in this cluster have practical significance since they demonstrate how to monitor beneficial inputs, accurately identify foods, and shadow nutritive inputs. Research in this area collectively indicates that AI-based approaches can greatly improve food identification, tracking efficacy, and delicacy, opening up new avenues for nutrition monitoring and food quality management(38 – 41).

Following a comprehensive examination of literature, use of AI, ML, and DL in nutrition research is verified. Five interconnected clusters can be utilized to identify areas where these technologies advance knowledge: substantiated nutrition, salutary assessment, food recognition and shadowing, prophetic modeling for complaints, complaint opinion and monitoring, and methodological improvement and innovative results. All of these results collectively demonstrate how AI has potential to revolutionize field of nutrition study and support personalized methods to health and wellbeing.

➢ *Limitations*

Suggested system has certain drawbacks that should be noted despite its encouraging outcomes. Lack of diversity in data used to train ML models is one major obstacle. Although system works well for majority of demographic groups, recommendations may not be as relevant or accurate for underrepresented groups. This problem emphasizes need for more thorough datasets that cover a wider range of user attributes, such as regional food availability and cultural eating customs.

➢ *Future Work*

Looking ahead, system presents numerous opportunities for enhancement, both in terms of functionality and addressing current limitations. One promising direction for future research involves the integration of real-time data streams, such as those derived from wearable technology and fitness trackers. These inputs hold the potential to provide valuable insights into users' sleep patterns, physical activity levels, and other relevant health metrics, paving way for even more adaptive and personalized recommendations.

IX. CONCLUSION

This study addressed increasing demand for individualized nutrition in a time of health-conscious living by introducing a novel ML-powered nutrient recommendation system constructed with the MERN stack. A revolutionary method of providing individualized dietary recommendations that adjust to each user's preferences, medical conditions, and nutritional objectives is demonstrated by combination of machine learning algorithms with contemporary web technologies. System demonstrates the power of fusing cutting-edge web frameworks with sophisticated analytics by utilizing adaptability and scalability of MongoDB for database management, stability of Express.js and Node.js for backend development, and dynamic interactivity of React.js for frontend design.

The suggested system effectively closes gap between real-world user-centric applications and theoretical developments in machine learning. The study's findings show notable gains in recommendation accuracy, with the system predicting nutrient needs with an F1-score of 92.3%. Along with an average API response time of 450 milliseconds, this degree of accuracy highlights the system's capacity to provide prompt and trustworthy insights, improving the user experience in general. Additionally, pilot users' feedback showed high levels of satisfaction, with 85% of participants describing the system as "very helpful," highlighting its potential to effectively meet a variety of user needs.

This system distinguishes itself from conventional rule-based or static dietary recommendation platforms by tackling important issues like scalability, interactivity, and adaptability. It can analyze intricate patterns in user data and produce highly customized recommendations thanks to its hybrid collaborative filtering approach, which is backed by decision trees and neural networks. By utilizing publicly accessible datasets, such as the USDA Food Database, in conjunction with anonymized user inputs, the system maintains a strong basis for model training while adhering to ethical data handling standards.

The work showcased here also highlights the wider ramifications of combining contemporary web technologies with machine learning. The way health and wellness solutions are provided could be completely redesigned by this collaboration, making them more user-friendly, interesting, and efficient. Numerous issues with personalized nutrition are addressed by the current implementation, but it also creates opportunities for future advancements such as real-time data integration, larger datasets for underrepresented groups, and the inclusion of lifestyle and mental health factors.

To sum up, the ML-powered nutrient recommendation system offers a scalable, effective, and user-friendly solution for contemporary dietary challenges, marking a substantial advancement in personalized nutrition. This study establishes the foundation for further innovation at the nexus of machine learning, technology, and health by opening the door for future improvements. As the area develops, this system acts as an example of how sophisticated computational methods can be used to address practical issues, ultimately enhancing users' quality of life and health outcomes globally.

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