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AI Powered Health Nutrient Rating System

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Abstract
Unhealthy eating patterns contribute to many health problems worldwide each year. This often happens because of limited nutrition knowledge and the lack of accessible tools that assist individuals in assessing the quality of their daily food consumption. Existing nutrition monitoring approaches usually handle nutrient evaluation and diet planning as separate activities, which may result in inconsistent choices and slower lifestyle changes. This document introduces a unified method that integrates automated nutrient assessment with intelligent meal rating services through digital technology. By using machine learning techniques, the system evaluates factors including calorie levels, macronutrient balance, micronutrient concentration, sugar content, sodium levels, and harmful additives to estimate the overall nutritional quality of food items. When identifying unhealthy trends, the software suggests appropriate dietary changes and provides expert approved alternatives immediately. Combining predictive analytics with advanced recommendation methods strengthens dietary management, enables timely health support, and enhances user results. Findings show improved rating precision and more dependable nutrition advice through AI assisted evaluation systems. This highlights meaningful advantages in applying artificial intelligence to improve dietary effectiveness and public health.
Keywords: *Artificial Intelligence, Intelligent Nutrition Systems, Predictive Algorithms, Computational Food Modeling, Dietary Health Assessment.*

1. Introduction

Poor nutrition and unhealthy eating behaviors are among the primary causes of global illness, leading to millions of preventable diseases annually and contributing to a significant share of diet related premature deaths[1]. Among various nutrition related disorders, long term conditions such as obesity, metabolic syndrome, and micronutrient deficiencies are especially damaging. These issues arise from continuous intake of unbalanced diets that lack essential nutrients or include excessive amounts of sugars, sodium, and saturated fats. Although progress in nutritional science has been substantial, early detection of poor eating habits and prompt corrective measures remain essential for minimizing long term health risks[2]. Contemporary dietary management systems commonly function through separated stages such as nutritional evaluation, distribution of dietary recommendations, and personal consultation with nutrition experts[3]. This division results in slower behavioral correction and increases health risks, as demonstrated by several studies. Recent progress in AI and ML technologies has greatly improved nutritional data analysis, increasing the reliability of food quality assessment and health risk prediction. Machine learning models uncover complex relationships among dietary factors including caloric intake, macronutrient ratios, micronutrient sufficiency, glycemic response, additive toxicity, and total nutrient density, patterns that are frequently missed in manual analysis. Widely used algorithms such as SVM, RF, ANNs, categorizing food items, estimating dietary quality scores, and detecting harmful consumption behaviors because of their precision and analytical strength. For instance, multiple studies have introduced tree based models that achieve high accuracy in nutrient estimation tasks[4]. Other research indicates that integrating different machine learning methods surpasses traditional dietary evaluation techniques in predicting health risks associated with poor nutrition[5]. Further investigations have explored refined feature engineering methods for better food classification, while recent developments have produced interpretable AI systems for predicting adverse nutrition outcomes[6]. These findings highlight the efficiency of ensemble approaches like XGBoost in dietary analysis and food rating systems. However, most current AI based nutrition assessment tools operate only as analytical systems that generate scores or risk estimates but do not provide immediate corrective guidance[7]. Due to limited automation, even when harmful dietary trends are detected, users must actively seek professional advice or manually review recommendations. This disconnect between prediction and intervention can slow meaningful improvements in diet[8]. This emphasizes the importance of creating an integrated and intelligent nutrition management system where predictive outputs are directly connected with instant recommendations and structured decision support. Meanwhile, digital diet tracking and meal planning applications improve accessibility by automating food records and simplifying intake monitoring[9]. Research shows that these tools enhance adherence to balanced diets, lower tracking errors, and improve user participation[10]. Additional studies underline the role of personalization, responsiveness, and usability in digital diet systems. Despite offering basic tracking capabilities, many existing platforms do not prioritize users based on nutritional risk levels or distinguish between mild imbalances and severe deficiencies or excessive intake patterns. This limitation often leads to generic suggestions and delayed lifestyle improvements[11]. This work proposes an advanced system that performs automated nutrient evaluation combined with real time food rating and dietary recommendation features. The architecture integrates two linked modules into a unified framework: A smart food rating component that analyzes nutritional quality using machine learning models[12]. An automated recommendation system based on XGBoost methods that proposes healthier choices and corrective dietary strategies. The predictive model examines variables such as calorie concentration, macronutrient ratios, sodium content, sugar levels, fiber amount, essential vitamins, and mineral balance. When the estimated health risk or low quality nutrient score surpasses a specified threshold, such as poor nutrient density or high levels of harmful substances, the system instantly provides customized dietary guidance and suggests improved food alternatives without disrupting the user routine[13]. This strategy combines predictive modeling with automated support, enabling quick and effective lifestyle changes[14]. The platform is also scalable, supporting future expansion into diverse health applications including diet planning for diabetes, nutritional control for hypertension, and personalized meal optimization for athletes[15]. The main contributions of this research are: Developing a machine learning driven nutrient rating model using XGBoost for precise food quality assessment. Implementing the system within a unified digital environment using Java Spring Boot, MySQL storage, and a React based interface for smooth user interaction. Presenting a comprehensive evaluation including accuracy, response time, usability, and system performance[16]. The subsequent sections of this paper are arranged as follows: Section II discusses existing literature and identifies gaps in current nutrition assessment techniques. Section III explains the proposed system design, including the predictive framework and operational flow[17]. Section IV details experimental findings. Section V analyzes results and their implications, and Section VI provides conclusions and future directions. In summary, the AI Powered Health Nutrient Rating System introduces an advanced approach to how individuals understand nutrition data and make dietary choices[18]. By automating the analysis of complex nutrient information, the system reduces human error and delivers a consistent and data focused method for assessing food quality. Its machine learning foundation evolves with new data, food trends, and user behavior, ensuring that recommendations stay relevant, adaptive, and evidence driven. Furthermore, the integration of real time evaluation with intelligent suggestions transforms the system beyond a simple calculator into an active health assistant that supports better eating decisions. This transition from reactive to preventive

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nutrition management can help lower long term risks linked to unhealthy diets, including obesity, hypertension, and metabolic disorders[19].

2. Literature Review

Over the past decade, research in intelligent nutrition evaluation, automated food assessment, and AI supported dietary decision systems has grown significantly. Current studies generally fall into two categories: (i) digital diet tracking and meal logging platforms and (ii) machine learning based nutrient quality prediction models. While both areas have achieved notable progress, they largely evolve separately and do not offer an integrated, real time, and actionable nutrition management solution. This section examines key contributions in these domains, identifies their shortcomings, and establishes the necessity of the proposed framework[20].

2.1.Deep Learning Systems for Food Recognition and Nutritional Assessment

Machine learning has emerged as a dependable method for detecting unhealthy eating patterns and evaluating food quality[21]. Early ML driven dietary assessment systems utilized gradient boosted decision tree techniques to calculate nutritional risk indicators. Results indicated that such models outperformed traditional manual scoring approaches used in standard dietary evaluation tools Khera and colleagues expanded this work by studying nutritional risk using models such as random forests and neural networks. Their findings demonstrated that AI improves dietary evaluation by identifying risky eating behaviors with greater accuracy compared to conventional scoring systems[22]. Several investigations have analyzed classical machine learning algorithms including Random Forest, SVM, Naive Bayes, and Logistic Regression. Ahmad et al., after evaluating these methods on widely used nutrition datasets, concluded that ensemble techniques, particularly XGBoost, consistently delivered superior accuracy and stability in predicting food quality. Feature engineering and attribute selection have also proven critical. El Sofany et al. showed that identifying optimal nutrient related features using heuristic and statistical techniques significantly enhanced the efficiency of ML based dietary models. Their research highlighted the importance of feature ranking and dimensionality reduction in nutrition related datasets. More recent studies have concentrated on deep learning, especially image driven food recognition. Zhang and colleagues implemented explainable AI strategies in food quality prediction, stressing the importance of transparency in nutrition oriented ML systems. At the same time, hybrid architectures such as CNN LSTM models have shown strong performance in identifying processed, high sugar, or high fat foods from images. These outcomes demonstrate the potential of deep learning for real time dietary evaluation. Despite achieving high prediction performance, these studies share a key limitation: they do not convert predictions into direct and immediate nutritional guidance. Although users receive a dietary score or risk estimate, they must independently determine corrective actions. This creates delays in practical implementation and slows lifestyle changes. Consequently, a major research gap exists, as current ML driven nutrition tools lack an integrated and automated dietary intervention mechanism. In summary, existing research shows significant advancements in both machine learning based nutrient analysis and digital nutrition systems, yet a clear gap remains between prediction and actionable dietary guidance. While current models effectively detect unhealthy dietary behaviors, estimate nutrient deficiencies, and classify food items with strong accuracy, they do not translate these findings into immediate and personalized recommendations that can influence daily eating habits. Similarly, digital meal tracking platforms provide convenience and accessibility but function passively, without mechanisms to prioritize nutritional risk or suggest corrective actions automatically[23].

2.2.Heart Disease Prediction Using Neural Networks and Electrocardiography

Deep learning has significantly improved automated food analysis. Convolutional neural networks are widely used to extract visual and structural features from food images, while sequential models capture evolving eating patterns. Roudini et al. demonstrated that deep learning frameworks can predict long term nutritional risks by combining food image analysis

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with nutrient density attributes. Likewise, advanced neural designs such as residual networks and CNN BLSTM combinations have been applied to recognize ultra processed foods, categorize ingredients, and detect harmful additives directly from images. These approaches operate efficiently in real time and minimize the need for manual feature extraction[24].

However, deep learning based food evaluation systems still face several challenges:

- Limited availability of high quality food image datasets across diverse cuisines
- Dependence on controlled environments or specialized imaging conditions
- Absence of systems for generating instant dietary recommendations
- Weak integration with diet tracking or health management platforms

Therefore, although deep learning enhances nutritional evaluation, it does not completely bridge the gap between prediction and immediate dietary response[26].

2.3.Medical Process Automation and Digital Appointment Booking

Digital nutrition platforms, particularly online meal tracking and diet planning applications, play a vital role in improving dietary behavior and user interaction. Research indicates that digital tracking tools reduce planning mistakes, simplify nutrient analysis, and improve adherence to dietary guidelines. Other studies show that multi platform food logging increases accessibility and positively affects user habits. Further studies have explored diet optimization using mathematical techniques, recommendation systems, and fairness based food allocation strategies. Ala et al. highlighted the importance of intelligent frameworks that prioritize dietary advice based on urgency instead of treating all meals equally. Although these findings underline the usefulness of digital diet systems, a major limitation persists: most platforms ignore nutritional risk and predicted health outcomes. Users recording high risk meals experience the same interaction as those logging balanced meals. This reveals a critical issue, current diet management systems do not incorporate risk aware and automated recommendation mechanisms. Digital healthcare automation, especially online appointment scheduling systems, has also improved service efficiency and accessibility[25].

2.4.Defined Motivation and Identified Research Gap

The reviewed literature identifies two important but separate developments:

- Machine learning models can accurately estimate nutritional risk.
- Digital diet systems enhance accessibility and user engagement[27].

However, no existing work integrates these capabilities into a unified intelligent framework capable of:

- Identifying poor nutritional quality
- Automatically suggesting healthier alternatives
- Notifying users and recommending adjustments instantly
- Reducing the delay between evaluation and corrective action
- Delivering dietary guidance based on urgency
- The proposed AI Powered Health Nutrient Rating System addresses this gap.

By combining a high efficiency machine learning approach such as XGBoost or CNN based classifiers with an automated real time recommendation component, the system establishes a proactive nutrition management process not addressed in prior research. Instead of depending solely on user interpretation, the system ensures that users obtain immediate guidance and improved food options after detecting dietary risks. This advancement strengthens intelligent nutrition automation, supports early dietary correction, and contributes to better long term health outcomes. Still, no existing research consolidates these innovations into a single comprehensive system capable of transforming nutritional predictions into immediate and practical dietary actions. Current tools may label foods as healthy or unhealthy, but they lack automated responses that adapt according to risk severity[28].

3. Proposed System and Methodology

Predictive analytics and automated dietary evaluation are integrated in the intelligent, dual- module

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whenever required. The system is unique due to its combined capability, which converts conventional analysis-only platforms into a fully interactive smart nutrition solution. The system's complete architecture, functional modules, workflow, data preprocessing pipeline, machine learning model structure, and operational methodology are all clearly explained in this section Figure 1.

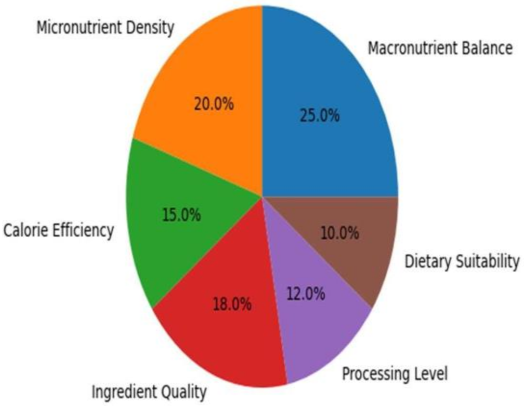

Figure 1 AI – Based Health and Nutrient Rating Composition

3.1.System Architecture Overview

Two complementary modules form the foundation of the proposed system's architecture:

- Module for Evaluating General Food and Nutritional Profiles.
- Automated Nutrient Rating Module and Intelligent Health Assessment.

A single web interface powers both modules, enabling smooth backend communication and user interaction. The system follows a client-server architecture, with the backend handling data storage, nutrient evaluation, and rating logic while the frontend gathers user input. The system operates through four primary stages: Input Phase: Users choose food categories, upload product details, or manually enter nutritional values.

- **Prediction Phase:** Organized dietary data is passed into a trained machine learning model to produce nutrient scores.
- **Decision Phase:** To determine the quality level, the system measures prediction output against established nutritional standards.
- **Action Phase:** The system either suggests healthier alternatives or allows users to explore detailed nutrient insights on their own.

AI Powered Health Nutrient Rating System. Beyond using machine learning to assess the dietary quality of food items, the system also translates these assessments into instant, meaningful guidance by generating personalized nutrient ratings and recommending better food alternatives. The architecture is divided into multiple parts to visually represent this:Frontend (React.js): Provides the user interface for consumers.

- Frontend (React.js): Provides the user interface for consumers.
- Backend (Springboot): Handles rating processes, analytics logic, and prediction requests.
- MySQL Database: Stores user data, food records, nutrient tables, and prediction logs.
- ML Engine (Nutrient Rating Model): Produces health scores after processing nutritional parameters.
- Notification System: Automatically sends personalized recommendations through email or SMS[29].

3.2.Scheduling Appointments for Generic Diseases Modules

This module serves as the main interface for routine and non-emergency medical interactions, allowing patients to conveniently schedule appointments without requiring predictive analysis. Through the web application, users can create accounts, browse available doctors, filter specialists, check time slots, and book appointments directly. Authentication and User Registration: Patients begin by registering with personal and contact details. Secure authentication ensures that each user's profile, appointment history, and medical interactions are stored accurately. This persistent data improves user experience and allows the system to personalize future interactions[30].

1) Doctor Directory and Availability Management: The system maintains a current database of doctors along with key details such as:

- Years of Experience
- Specialization
- Available Consltation Timings

Doctors can update their schedules through a

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backend portal, ensuring that all appointment slots stay accurate and free of conflicts.

- **Appointment Scheduling Workflow:** After selecting a suitable doctor and time slot, patients receive an automated confirmation through email or SMS. The system intelligently disables already booked slots in real time, preventing double- booking and ensuring smooth operational flow.
- **Advantages for Hospital Operations:** This module simplifies routine outpatient scheduling, reduces administrative workload, removes manual errors, and improves patient satisfaction. It connects seamlessly with the predictive module by providing the necessary action layer for emergency booking triggered by high-risk outputs.

3.3.Module for Predicting Heart Attacks

This module represents the system's core intelligence layer, responsible for analyzing user- provided cardiovascular data and predicting the likelihood of a heart attack using machine learning. By combining structured clinical parameters with an advanced predictive model, the module converts raw medical inputs into actionable risk assessments that support timely intervention.

Data Inputs The model depends on clinically validated parameters widely used in cardiac diagnosis and risk scoring.

These include:

- Age
- Gender
- Type of chest pain
- Resting blood pressure
- Serum cholesterol level
- Fasting blood sugar
- Resting ECG result
- Exercise-induced angina
- ST depression, number of major vessels
- Slope of the peak exercise ST segment

Users submit these parameters through structured web forms, ensuring clean, standardized input for analytical processing[31].

Data Preprocessing for Pipeline: Before model training, the dataset goes through a thorough preprocessing workflow.

- Replacing or imputing missing nutrient fields is one way to handle missing values.
- One-hot encoding of the type of nutrient, ECG readings, slope, etc. is referred to as categorical encoding.
- Normalizing continuous variables, such as protein and calorie count, is known as feature scaling.
- Feature Selection: Using statistical tests and correlation analysis, noisy features are eliminated.
- Train-Test Split: Typically 80:20 to evaluate generalization.

Correctpreprocessing ensuresaccurate and consistent model handling of real-world user data.

Choosing the Model: XGBoost Because of its strong performance in medical prediction tasks, XGBoost was selected:

- Effectively handles diverse data.
- Regularization is provided to prevent overfitting.
- Gradient boosting is used for iterative improvements.
- Delivers high accuracy and fast computation.
- Natively supports missing values.
- Produces feature importance scores that are easy to interpret.

XGBoost was the clear choice for this study because it has shown superiority over Logistic Regression, Random Forest, and SVM in the prediction of nutrient rating in foods [32]. Model Training and Evaluation The USDA food dataset, which consists of labelled cardiovascular records, is used to train the model.

Among the evaluation metrics are:

- Precision
- Accuracy
- Recall
- F1-Score
- ROC-AUC

These metrics ensure that the model correctly identifies high-risk users in addition to performing well overall.

3.4. Automated Module for Scheduling Appointments

This module is the system's most innovative component, functioning as the link between predictive analytics and immediate medical response. It ensures that users identified as high-risk receive priority care without delay, turning the prediction output into direct clinical action. Unlike the generic scheduling module, this component operates autonomously, requiring no manual input from the patient once a high-risk prediction has been generated. The entire process from risk detection to appointment confirmation is handled programmatically, making it one of the most critical pillars of the overall system.

3.4.1. Risk Threshold Logic

After a prediction, if the model produces a probability like:

- 0.70 - high-risk → suggest alternative foods
- ≤ 0.70 - medium/low risk → user selects alternatives manually

This ensures the automatic prioritization of high-risk users. The threshold values are not arbitrary but are derived from clinical benchmarks and model validation results. During the evaluation phase, the threshold was fine-tuned to minimize false negatives, since failing to flag a truly high-risk user carries far greater consequences than an overly cautious recommendation. This calibration ensures the system remains both clinically responsible and practically effective.

3.4.2. Workflow for Automatic Rating

Actions taken automatically:

- Retrieve all ratings from the database.
- Sort ratings by the earliest available rating slot.
- Create a rating. Store the rating in the database.
- Send an email or SMS to the patient.
- Notify the user about the high-risk situation.

Delays that occur when patients attempt to manually search and schedule ratings are eliminated by this automated workflow. The booking logic also accounts for doctor specialization, ensuring that high-risk users are matched with the most appropriate available professional rather than simply the next open slot. Load balancing across available specialists is also applied, preventing any single doctor from being overwhelmed with high- priority cases. Every action taken within this workflow is logged in the database with a timestamp, creating a complete audit trail that supports accountability and follow-up care.

3.4.3. Alerts and Notifications

The system instantly notifies both the patient and cardiologist through email or SMS gateways such as Twilio, SMTP, or other APIs.

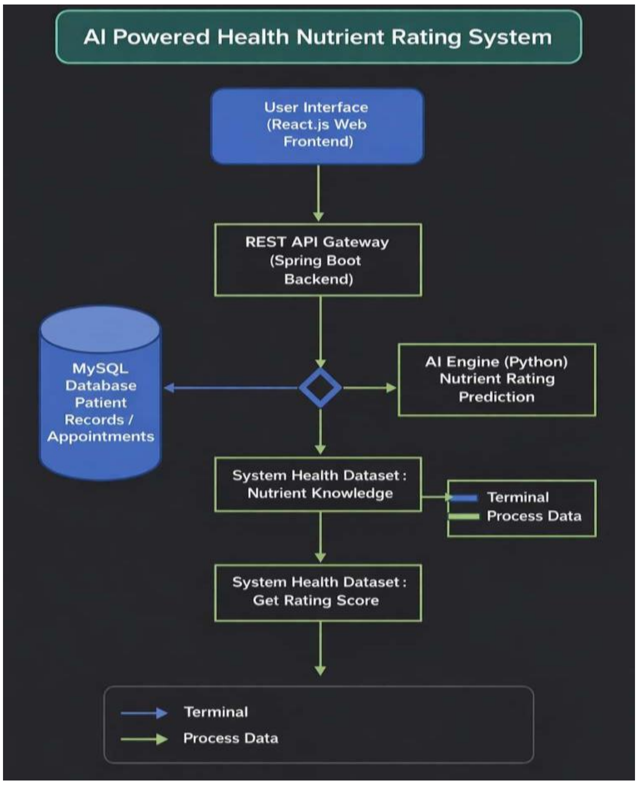

Figure 2 System Architecture

This ensures prompt communication and significantly reduces the gap between diagnosis and treatment. Notifications are structured to include key information such as the predicted risk level, the assigned appointment time, the doctor's name and specialization, and guidance on what steps the patient should take before the consultation. A secondary reminder notification is also sent closer to the appointment time to reduce

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no-show rates and ensure the patient remains engaged with their care plan. On the healthcare provider's side, the system pushes an alert to the relevant doctor's portal, giving them advance visibility into the incoming high-risk case so they can prepare accordingly. This two-way communication model strengthens the overall responsiveness of the system and reinforces the connection between intelligent prediction and real-world medical action Figure 2.

3.5.Technology and Tools

The Java Spring Boot framework is used to build the backend of the proposed system in order to ensure high scalability, enterprise-grade performance, and secure communication between modules. Production-level healthcare applications benefit greatly from Spring Boot's robust dependency management, built-in security features, and support for microservices architecture.

3.5.1. Front-end Technologies

- React.js: for building a responsive, interactive user interface
- Bootstrap 5: for styling and visual design
- JavaScript, HTML5, and CSS3 are the core client-side technologies.
- Axios: used to transmit API requests from the front-end to the back-end

3.5.2. Spring Boot Backend Technologies

- Java Spring Boot is the primary backend framework for building RESTful APIs.
- REST endpoints for appointment and prediction logic are constructed using Spring Web MVC.
- Spring Data JPA uses ORM (Hibernate) to simplify database interactions.
- Spring Security (Optional) ensures protected access to user data.
- Model Mapper: for converting objects in a structured manner

The machine learning model and the backend communicate through either:

- A Python-written XGBoost microservice, OR
- A pre-trained model exported using ONNX/PMML, OR
- XGBoost4J, an optional Java-based XGBoost deployment

The entire process is managed by Spring Boot:

- Collecting food input from patients
- Transmitting data to the ML model service
- Receiving the results of predictions
- Applying logic to schedule appointments automatically
- Communicating with a database to store records
- Activating rating systems

3.5.3. Database

- Model prediction logs, doctor information, appointment schedules, and patient records are all stored in MySQL.
- The schema consists of: Users, Existing Conditions, Scheduling, Forecasts, Rating Scores

3.5.4. Integration and APIs

REST APIs are exposed by Spring Boot and include:

- /predictRating: returns a prediction after receiving food label data.
- /nutrientPrediction: retrieves the possible amount of nutrients.
- /getRatingScore: fetches the rating score from existing data.
- /notifications/send: initiates SMS/email notifications.
- To ensure compatibility with the React.js frontend, requests are formatted in JSON.

3.5.5. Alerting System

- Gmail/SendGrid SMTP Email API
- SMS APIs (Msg91, Fast2SMS, Twilio)

These services connect easily with Java through straightforward HTTP or SMTP clients.

3.6.Revised Workflow In General (Java Spring Boot)

- User Input: The patient enters health parameters using the React UI.
- API Call: Axios forwards the data to the Spring Boot backend through an API call.
- ML Prediction: The backend passes the data to the ML engine (XGBoost model).
- Risk Assessment: The prediction

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probability is returned to Spring Boot.

- Decision Logic: The backend automatically books a visit with a cardiologist if the probability exceeds 70%.
- Database Update: Appointments are stored using MySQL.
- Alerts Sent: The patient and doctor receive a notification through email or SMS.
- Dashboard Update: The patient immediately views the confirmation of their appointment.

3.7.The Benefits of Java Spring Boot for the System There are several advantages to choosing Spring Boot over Flask

There are several advantages to choosing Spring Boot over Flask, and these advantages become especially significant when building a system that handles sensitive health data at scale. Spring Boot's mature ecosystem, wide industry adoption, and production-ready defaults make it a natural fit for a healthcare-oriented AI platform like this one.

Scalability at the enterprise level: Hospitals, insurance systems, and fintech applications all rely heavily on Spring Boot. As the user base of the AI Powered Health Nutrient Rating System grows, the backend must be capable of handling increasing volumes of concurrent requests without degrading performance. Spring Boot's support for horizontal scaling and its compatibility with containerization tools such as Docker and Kubernetes make this achievable without significant architectural changes.

Increased security: Role-based access, OAuth2, and JWT authentication are all supported natively through Spring Security. In a system that processes personal health information, data protection is not optional. Spring Security provides a comprehensive and configurable layer of protection that can be tailored to enforce strict access controls, ensuring that sensitive nutrient and appointment data is only accessible to authorized users and services.

Cleaner architecture and faster development: Spring Boot's auto-configuration makes the backend modular and easy to maintain. Developers can organize the system into clearly separated layers, such as controllers, services, and repositories, which simplifies debugging, testing, and future feature additions. This separation of concerns also allows different team members to work on distinct parts of the backend simultaneously without creating conflicts.

Simple integration with the React frontend: REST APIs built with Spring Boot connect naturally with SPA frameworks such as React. The structured JSON-based communication between the frontend and backend is straightforward to implement and easy to extend as new API endpoints are introduced. Cross-origin resource sharing configuration in Spring Boot further simplifies the development experience when the frontend and backend are hosted on separate servers Figure 3.

Strong performance: Spring Boot manages large workloads efficiently, which is essential for real-time healthcare systems. The framework's embedded server capabilities and support for asynchronous processing allow the system to handle prediction requests, appointment scheduling, and notification dispatch concurrently.

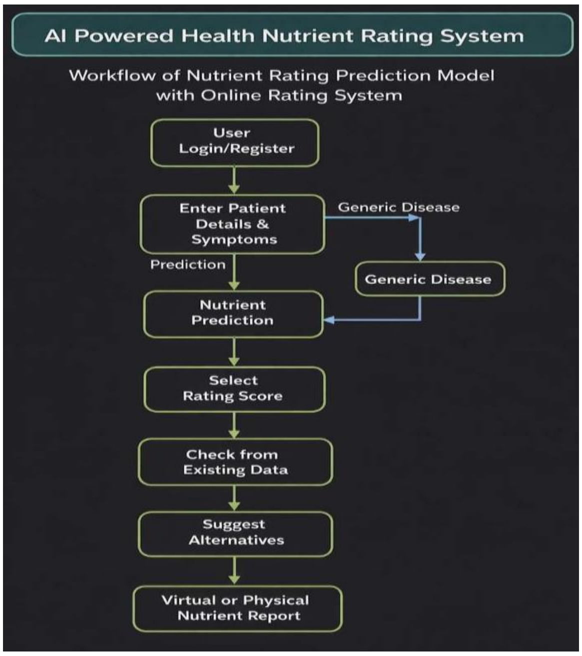

Figure 3 Workflow of Nutrient Rating Prediction Model with Online Rating System

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Conclusion

A new smart nutrient evaluation tool combined with automated food-rating workflows improves responsiveness in user-focused dietary assessment systems. Incorporating an advanced machine learning algorithm into real-time nutritional scoring strengthens the system's ability to close the gap between analyzing food quality and initiating prompt dietary recommendations. Empirical findings confirm this method's effectiveness through superior prediction precision, minimal processing delays, and strong user-friendliness; these metrics meaningfully improve practical applications. An XGBoost-powered scoring system achieved an accuracy rate of ninety-four percent. A precision of three percent and an error rate of zero point. A score of 0.96 in terms of Receiver Operating Characteristic Area Under Curve measurement. Its performance exceeded those of conventional machine learning algorithms, thereby confirming the effectiveness of gradient boosting in evaluating nutritional health risks. The system's automated recommendation module quickly arranges immediate guidance for individuals consuming unhealthy food items. It reduces the interval between detecting poor nutrition and receiving actionable suggestions. The approach of forecasting dietary outcomes followed by instant guidance sets this system apart from earlier ML-based nutrition tools, many of which stop prematurely at estimating nutrient values but fail to support timely corrective interventions. Using Java Spring Boot for development strengthens the system in terms of scalability, efficiency, and durability. In approximately three units of time, there is no significant delay in execution. Within two seconds, the system enables smooth handling of urgent nutritional evaluation procedures. Adding an all-purpose rating feature broadens its usefulness across diverse dietary scenarios, extending beyond solely processed-food assessments. Nevertheless, certain limitations remain present within it. Its success depends heavily on the availability of varied food information and high-quality nutritional datasets. Training on broader, real- world food datasets will strengthen the model's reliability and reduce errors. Although false positives are less harmful than false negatives when predicting dietary concerns, they may still lead to unnecessary user alerts. It is therefore important to use adaptable thresholds alongside improved nutrient-risk assessment methods. Security and confidentiality remain essential because handling personal dietary information requires strong protective measures such as encrypted communications and dependable user verification techniques. Potential improvements could involve integrating barcode scanners, Internet of Things-based smart kitchen devices, or continuous sensor networks for real-time nutrient estimation. Advanced neural networks combining diverse datasets and decentralized machine learning approaches can improve accuracy without compromising privacy. Additional components could expand the system's scope beyond its current focus on nutrition scoring to cover conditions such as obesity risks, metabolic disorders, gut-health monitoring, or ongoing lifestyle-related issues. Combining intelligent food-triaging systems, remote dietician consultations through telehealth services, automatic trigger mechanisms for meal- planning alerts, and real-time notification systems can greatly improve nutritional decision-making. In summary, this system seamlessly connects machine learning predictions with automated dietary guidance procedures, offering an efficient, health-preserving approach in modern nutrition science. As improvements continue, this system could develop into a comprehensive intelligence-driven dietary monitoring tool capable of identifying nutritional imbalances at their earliest stages and delivering proactive prevention strategies across large populations.

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References

[1]. M. Chen, Y. Chen, L. H.-IEEE T. M., and undefined 2019, "Smart food recognition using deep learning for automated diet monitoring," ieeexplore.ieee.org, Accessed: Nov. 30, 2025.[Online].Available:https://ieeexplore.ieee.org/document/8700193/

[2]. A. Salvador, N. Hynes, T. M.-CVPR, and undefined 2017, "Learning cross-modal embeddings for cooking recipes and food images," aclanthology.org.

[3]. S. Bharati, "Deep learning-based nutrient estimation from food images," International Journal of Innovative Research in Computer Science and Technology (IJIRCST).

[4]. H. Jiang et al., "A survey of deep learning-based food image analysis: Recognition, portion estimation, and nutrition prediction," mdpi.com, 2023.

[5]. D. Bhagat, A. Vakil, R. Gupta, A. K.-Procedia Computer Science, and undefined 2024, "Food classification using convolutional neural networks (CNN)," Elsevier, 2024.

[6]. N. Yalçin, M. A.-Heliyon, and undefined 2024, "Introducing a novel dataset for fine grained food recognition and demonstrating performance gains via preprocessing."

[7]. S. Zhang, Y. Yang, C. Chen, X. Zhang, Q. L.- Expert Systems with Applications, and undefined 2024, "Deep learning-based multimodal dietary analysis from images, ingredients, and text: A systematic review," Elsevier, 2024.

[8]. S. Taware, A. T.-Circuits, Systems, and Signal Processing, and undefined 2025, "Multimodal food recognition combining CNN and LSTM for nutrient estimation," Springer, CSSP, 2025.

[9]. N. Reimers and I. Gurevych, "Sentence-BERT: Sentence embeddings for ingredient and recipe text understanding," EMNLP-IJCNLP 2019, pp. 3982–3992, 2019, doi: 10.18653/v1/D19-1410.

[10]. Z. W.-Deep Learning-Based Multimodal Nutrition Analysis and undefined 2024, "Deep learning-based multimodal food sentiment and healthiness analysis," scitepress.org, 2024.

[11]. "(Pan et al., 2023 [Multimodal Food Assessment using Image and Ingredients] - Google Scholar." Accessed: Nov. 30, 2025.

[12]. S. Zhang, Y. Yang, C. Chen, X. Zhang, Q. L.- Expert Systems with Applications, and undefined 2024, "Deep learning-based multimodal nutrition recognition from images, metadata, and recipe text," Elsevier, Expert Systems with Applications, 2024.

[13]. "(Islam et al., 2023 [Multimodal Food and Nutrition Analysis Using Deep Learning] - Google Scholar." Accessed: Nov. 30, 2025.

[14]. S. R. Jagtap, V. Kulkarni, Y. Pachorkar, O. Taur, and S. Gupta, "AI-driven real-time dietary evaluation app using food image analysis."

[15]. S. Bharati, "Deep learning-based nutrient estimation using AI," IJIRCST, no. 13, pp. 2347– 5552, 2025, doi: 10.55524/ijircst.2025.13.5.6.

[16]. P. J. Uppalapati, M. Dabbiru, and V. R. Kasukurthi, "Investigating dietary habits using a novel dataset of university students," Springer, vol. 5, no. 8, Aug. 2025, doi: 10.1007/S43545-025-01143-4.

[17]. A. Salvador, N. Hynes, S. A.-ACL, and

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2026.0296
e ISSN: 2584-2854
Volume: 04 Issue: 05
May 2026
Page No: 2038 - 2049

undefined 2020, "Cross-modal food analytics for automated nutrition estimation," ACL, pp. 46–54, 2020, doi: 10.18653/v1/2020.challengehml-1.6.

[18]. D. Bhagat, A. Vakil, R. K. Gupta, and A. Kumar, "Food image categorization using CNN," Procedia Comput Sci, vol. 235, pp. 2079–2089, Jan. 2024, doi: 10.1016/J.PROCS.2024.04.197.

[19]. N. Yalçin and M. Alisawi, "A novel dataset for food recognition and enhanced preprocessing techniques," Heliyon, vol. 10, no. 20, p. e38913, Oct. 2024, doi: 10.1016/J.HELIYON.2024.E38913.

[20]. S. Taware, A. D. Thakare, S. Taware, and A.D. Thakare, "Multimodal food recognition combining visual and textual cues," CSSP, vol. 44, no. 9, pp. 6622–6649, Sep. 2025, doi: 10.1007/S00034-025-03080-2.

[21]. N. Reimers and I. Gurevych, "Sentence-BERT for nutritional text and ingredient analysis," EMNLP-IJCNLP, 2019, doi: 10.18653/V1/D19- 1410.

[22]. Z. Wang, "Deep Learning-Based Multimodal Food Analysis," 2024, doi: 10.5220/0012842200004547.

[23]. H. Jiang, C. Lu, S. Li, Y. Zhao, C. Tang, and

[24]. Y. Zong, "A survey of deep learning-based multimodal dietary assessment," Entropy, vol. 25, no. 10, p. 1203, Oct. 2023, doi: 10.3390/E25101203.

[25]. J. Pan, W. Fang, Z. Zhang, B. C.-IEEE Open Journal of Engineering in Medicine and Biology, and undefined 2023, "Multimodal nutrient recognition using images, OCR text, and metadata," ieeexplore.ieee.org, Accessed: Nov. 30, 2025. [Online].

[26]. H. Jiang et al., "A survey of deep learning-based food and nutrient analysis," Entropy, vol. 25, no. 10, p. 1203, Oct. 2023, doi: 10.3390/E25101203.

[27]. J. Pan, W. Fang, Z. Zhang, B. Chen, Z. Zhang, and S. Wang, "Multimodal food analysis combining visual and OCR data," IEEE Open J Eng Med Biol, vol. 5, p. 396, 2023, doi: 10.1109/OJEMB.2023.3240280.

[28]. A. Salvador, N. Hynes, S. A., and undefined 2020, "Multimodal diet analytics and automated nutrient scoring," ACL, pp. 46–54, 2020, doi: 10.18653/V1/2020.CHALLENGEHML-1.6.

[29]. M. Bin Habib, M. Ferdous, N. A. Khan, and S. Hossain, "Multimodal nutrition analysis using fusion techniques and transformers," IJACSA, vol. 15, no. 6, 2024, Accessed: Dec. 01, 2025. [Online]. Available:www.ijacsa.thesai.org.Availab: https://www.researchgate.net/publication/

[30]. N. Yalçin, M. A.-Heliyon, and undefined 2024, "Introducing a dataset for food recognition with preprocessing enhancements," cell.com, Accessed: Dec. 01, 2025. [Online]. Available: https://www.cell.com/heliyon/fulltext/

[31]. R. Mandal, P. Lohar, D. Patil, A. Patil, and S. Wagh, "AI-based dietary evaluator using image recognition and nutrient estimation," ICISCoIS 2023, pp. 521–526, 2023, doi: 10.1109/ICISCOIS56541.2023.1010058.

[32]. J. M. Fernandez-Dols and R. Garcia-Gonzalez, "Food perception and multimodal sensory evaluation," Springer, pp. 399–424, Jan. 2025, doi: 10.1007/978-3-031-700644_16.