

NutriMatch: AI – Driven Personalized Meal Recipes based on the Fresh Ingredients’ Detection and User’s Dietary Needs

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Abstract— In modern fast-paced lifestyles, maintaining a healthy diet is challenging, contributing to the rise of diet-related diseases and food wastage, particularly fresh produce. Existing digital meal planning systems often lack the robustness to integrate practical ingredient detection with personalized dietary requirements effectively. To address these issues, this paper introduces NutriMatch, a web-based application designed to provide personalized healthy meal suggestions based on user submitted images of fresh fruits and vegetables. NutriMatch integrates an ingredient detection interface where users upload produce images via the browser, and the system returns the predicted ingredient label with a confidence score, for example, ginger with 90%, enabling users to verify detection before receiving tailored recipe recommendations. The system utilizes the MobileNetV2 architecture to classify 36 categories of fresh ingredients, chosen for its efficiency and suitability for web-based deployment. The platform is developed using the Laravel framework with PHP and MySQL for backend management, while the frontend utilizes React for a responsive user interface. Experimental results on the test dataset demonstrate that the model achieves a precision of roughly 92 percent and an F1-score of 0.89, validating the system's ability to facilitate sustainable eating habits and personalized nutrition through artificial intelligence model.

Keywords—Artificial Intelligence, Image Recognition, Personalized Nutrition, Web Application, MobileNetV2

I. INTRODUCTION

With a global rise in diet-related health problems such as obesity, diabetes, and malnutrition, the need for healthy eating is more critical than ever. Currently, individuals often lack detailed insights into utilizing fresh produce, leading to spoilage. Fruits and vegetables are essential for a balanced diet, yet their potential is often unrealized due to a lack of cooking skills or time constraints.

The primary problem motivating this project is the limitation of current recipe applications. While many apps aim to assist in meal planning, they often fail to effectively bridge the gap between abstract meal ideas, and the actual ingredients users possess at home. Furthermore, existing digital meal planning systems often lack the technological robustness to offer features like automated ingredient detection or seamless dietary personalization. NutriMatch aims to resolve these issues by offering a smart, AI-powered ecosystem that empowers users to maximize their fresh produce usage. By recommending personalized, health-aware recipes based on available ingredients and individual health goals, the system promotes both personal wellness and environmental sustainability.

This paper presents the design and development of NutriMatch, a web-based system that supports sustainable eating habits through personalized nutrition assistance.

NutriMatch integrates AI-powered image recognition to detect food items from user-submitted images and combines this with an automated recipe recommendation module that filters and tailor's recipe suggestions to individual needs and preferences.

II. RELATED WORKS

A. Automated Recognition and Classification of Fruit and Vegetables

The development of deep learning models for identifying and categorizing produce has become essential for industrial and commercial applications, particularly in supermarkets and processing factories [1]. To address the variability found in real-world environments, such as lighting changes and background variations, researchers have proposed various high-precision frameworks for example Robust DCNN Frameworks. One study introduced a simple and efficient Deep Convolutional Neural Network (DCNN) designed to distinguish natural fruit images in difficult scenarios [2]. By utilizing a specialized database of 20 categories (comprising 10,000 images) from the Gilgit-Baltistan region of Pakistan, the model achieved a 96% recognition accuracy, demonstrating its readiness for global application requirements

Research also works on the optimized CNNs and freshness detection. Utilizing Keras and TensorFlow, researchers built an optimized CNN architecture featuring five convolutional and pooling layers [1]. This model was specifically trained to identify fresh versus rotten produce across six classes, achieving a high accuracy of 96.88%. Furthermore, the model proved its versatility by maintaining a 94.35% accuracy when tested on the more extensive Fruits 360 dataset, which contains 131 categories

Beyond mere identification, research into YOLOv3 and optimized GoogLeNet has focused on maximizing efficiency for real-time industrial use [3]. By reducing the number of convolutional kernels and training parameters by 48%, researchers successfully tripled training speeds from 11.38 to 33.68 sheets per second. These technical refinements were particularly effective at distinguishing between produce items that are nearly identical in shape and color, such as lemons and oranges, which often pose significant challenges for traditional recognition systems.

B. Dietary Monitoring and Nutritional Health

Researchers developed MyDietCam, a mobile app for healthy Malaysian adults that integrates automated food recognition to ease the burden of manual dietary logging. It provides individualized recommendations and generates a diet quality score based on the Malaysian Healthy Eating Index [4].

A cross-sectional study of 2,509 adults used Principal Component Analysis (PCA) to identify five distinct eating behavior groups. The research found significant gender differences, noting that men consume more meat and engage in strength sports, while women adhere more to structured, vegetable-rich diets [5].

For Multi-food Detection on Plates, this research treats food analysis as a multi-class object detection problem because plates often contain multiple food items [6]. It evaluates models like YOLOv5 to accurately identify components of meals to support nutritional health tracking

C. Optimization of Deep Learning Architectures

Research by Sandler et al. [7] introduces MobileNetV2 architecture, a new mobile-tailored architecture using inverted residuals and linear bottlenecks. It significantly decreases the required memory and computational operations while maintaining high accuracy for object detection and semantic segmentation on resource-constrained devices.

One study compares YOLOv5 and EfficientDet across various food datasets for comparative performance analysis, concluding that YOLOv5 provides superior performance in both accuracy (mAP) and response time [6].

In terms of speed and efficiency Improvements, efforts to optimize GoogLeNet resulted in reducing the number of training parameters by 48%, which increased the training speed from 11.38 to 33.68 sheets per second [3].

D. Comparative Analysis with Existing Platform

A comprehensive review of existing platforms reveals a distinct gap in current market solutions, particularly regarding the integration of real-time image scanning with personalized recipe generation. We conducted a comparative analysis of NutriMatch against prominent existing systems such as MyFitnessPal [8], PlateJoy [9], and SuperCook [10].

MyFitnessPal is widely recognized for its robust calorie tracking capabilities; however, it relies heavily on manual data entry and lacks any form of ingredient image detection. Similarly, PlateJoy offers excellent personalized meal planning services but necessitates that users manually input their pantry inventory, which can be tedious and time-consuming. On the other hand, SuperCook succeeds in suggesting recipes based on listed ingredients but does not incorporate AI-driven health tracking or deep personalization for dietary restrictions. NutriMatch addresses these identified limitations by synthesizing the strengths of these platforms. It combines the convenience of automated ingredient detection with the utility of personalized recipe creation and nutritional tracking, offering a more holistic solution for sustainable nutrition management.

Table I summarizes the functional differences between these platforms, highlighting NutriMatch's unique position as the only system integrating real-time detection with health tracking. Across the four platforms, NutriMatch stands out as the most comprehensive: it supports real-time monitoring, recipe generation, and uniquely offers ingredient detection whereby this is a feature missing in MyFitnessPal, PlateJoy, and Supercook.

TABLE I
COMPARISON BETWEEN NUTRIMATCH AND OTHER WEB SYSTEM

Criteria	MyFitnessPal [8]	PlateJoy [9]	Supercook [10]	NutriMatch
Real-time Monitoring	Yes	No	No	Yes
Recipe Generation	No	Yes	Yes	Yes
Ingredient Detection	No	No	No	Yes
Calorie Tracking	High	Medium	Low	High
Food Waste Focus	Low	Low	High	High

III. METHODOLOGY

The development of NutriMatch adheres to Agile Methodology. This iterative approach was selected due to the complex nature of integrating Artificial Intelligence with web development. The Agile framework allows for continuous refinement of the AI model and user interface through repeated cycles of planning, designing, developing, and testing.

A. System Design

The system architecture is designed to operate seamlessly within a web browser environment. The workflow begins when users interact with the frontend interface to upload photographs of their ingredients. These requests are transmitted to the backend server, which orchestrates communication between the database and the AI processing module.

Fig. 1 illustrates the core user interactions within the system, such as uploading ingredient images, viewing detection results, and generating personalized meal recommendations. This structure ensures that heavy computational tasks, such as image classification, are handled on server-side to maintain a smooth user experience.

As shown in Fig. 2, the NutriMatch system flow starts with user authentication to ensure secure access. After a successful login, the user uploads an ingredient image which is processed by the ingredient detection module. Once an ingredient is detected, the result is displayed to the user who may optionally add additional ingredients. The system then retrieves the user's dietary preferences and profile data to generate personalized recipe recommendations. Finally, the selected recipe contributes to the calorie tracking process, allowing users to monitor their daily nutritional intake before the process ends.

B. Implementation Stacks

The development employs a robust technology stack ensuring scalability and high performance. The frontend is constructed using the React library, which allows for the creation of a dynamic and responsive user interface featuring a modern, green-themed aesthetic suitable for a health application. For the backend, the Laravel framework is utilized to manage server-side logic, including secure user authentication and database management. This separation of concerns ensures that the application remains maintainable and scalable as the user base grows.

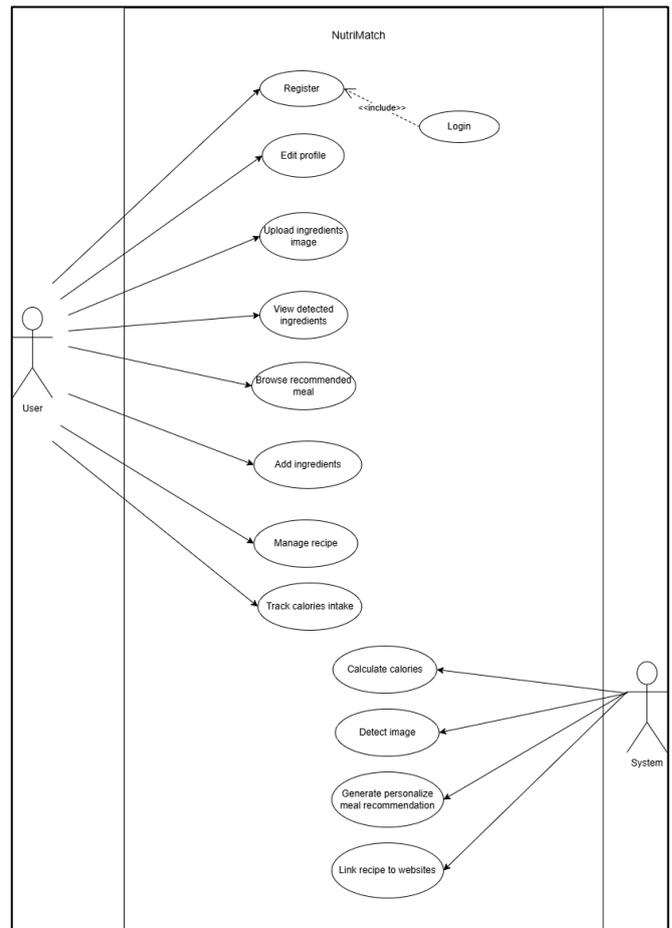


Fig. 1 Use Case Diagram

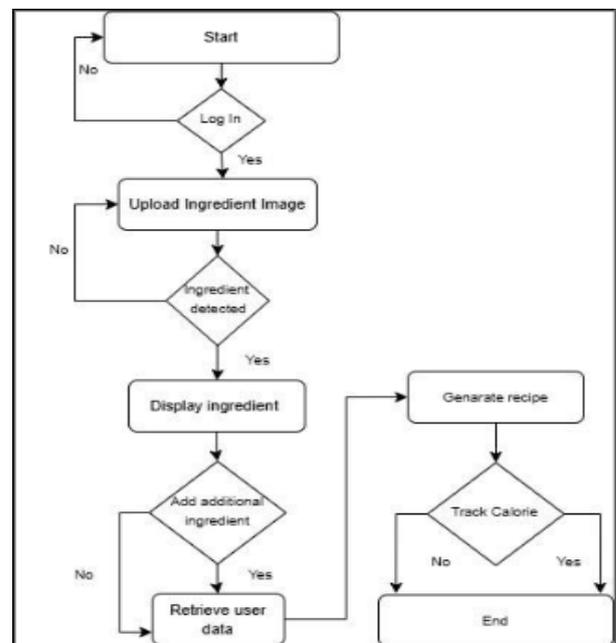


Fig. 2 NutriMatch FlowChart

C. Machine Learning Implementation

The core intelligence of the NutriMatch system relies on a deep learning model designed to classify fresh produce from user-uploaded images. For this purpose, the MobileNetV2 architecture was selected due to its lightweight design and computational efficiency, making it suitable for web-based deployment where system resources may be limited.

The model was developed using the TensorFlow and Keras frameworks and trained on an image dataset consisting of 36 distinct categories of fruits and vegetables. The dataset was already organised into separate training, validation, and testing folders by the data provider. Specifically, each category contained 100 images for training, 10 images for validation, and 10 images for testing, resulting in an approximate split of 83% for training, and 8% each for validation and testing. This predefined dataset structure was used directly during model training and evaluation, without additional manual data splitting.

The development process employed Transfer Learning to expedite training and improve accuracy. A pretrained MobileNetV2 backbone, initialized with ImageNet weights, was utilized as the feature extractor. To adapt the model for NutriMatch, the top classification layers were removed and replaced with a global average pooling layer, followed by fully connected dense layers with ReLU activation, and a final Softmax output layer with 36 neurons corresponding to the target classes. During the training phase, the base layers of the MobileNetV2 model were frozen to retain the learned features from ImageNet, while only the custom classification layers were trained.

Data preprocessing was a critical step in the pipeline. All input images were resized to a standard resolution of 224 × 224 pixels to match the architecture requirements. To prevent overfitting and enhance the model's ability to generalize unseen data, data augmentation techniques were applied, including random rotation, zooming, horizontal flipping, and shearing. The trained model was eventually saved in the .h5 format and integrated into the system via a FastAPI service, allowing for real-time inference requests from the main application.

IV. RESULTS AND SYSTEM PROTOTYPES

This section presents the fully developed prototype of NutriMatch and discusses the results of the system testing. The user interface was meticulously designed to be intuitive, ensuring that users can easily navigate from registration to recipe generation.

A. Registration and Personalization Module

The user journey begins at the Registration and Personalization interface. Unlike standard sign-up forms, NutriMatch requires users to create a detailed profile that

captures essential personal metrics, dietary preferences (such as Vegan, Keto, or Paleo), and specific health goals. This data is critical as it feeds into the personalization engine. Fig. 3 illustrates the dietary preference selection screen, where users configure their specific restrictions and cuisine interests to tailor future recommendations.

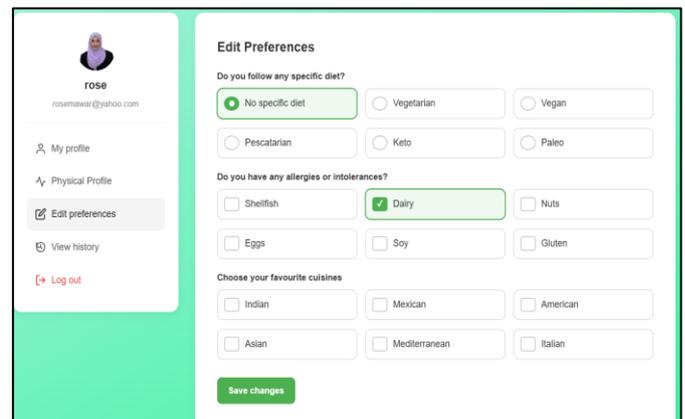


Fig. 3 User Profile based on preference

B. Dashboard and Calorie Tracker

Upon logging in, users are greeted by the Main Dashboard. This central hub features a visually engaging real-time calorie tracker, displayed as a dynamic progress ring. The dashboard is designed to provide a quick health overview briefly, encouraging users to stay within their nutritional goals. Fig. 4 shows the Calorie Tracker Ring that updates in real time as users log meals, visualizing the percentage of the daily calorie goal achieved. This provides users with instant feedback on their nutritional intake.

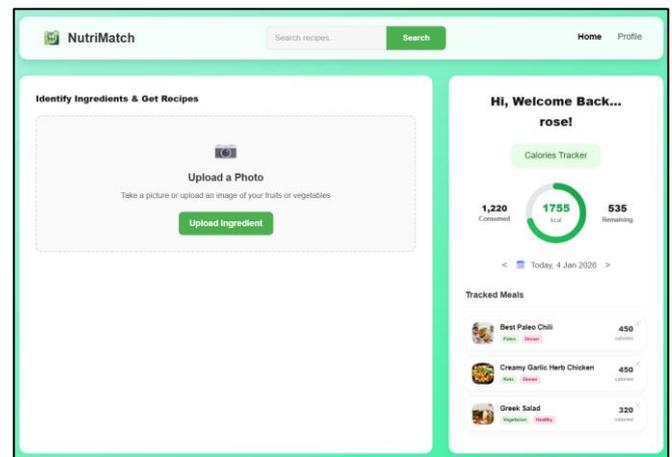


Fig. 4 Real-time calorie tracker ring on the dashboard

Fig. 5 shows the system generates a Random Recipe Recommendation list directly on the dashboard. This section offers immediate meal inspiration without requiring any user input, helping users decide what to cook quickly.

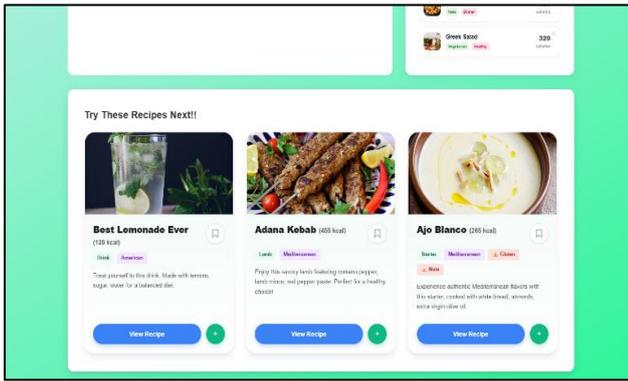


Fig. 5 Random Recipe Recommendation

C. Ingredient Detection

The core feature of the application is the Ingredient Detection Interface. In this module, users upload an image of their fresh produce directly through the browser. The system processes this image using the integrated MobileNetV2 model. Fig. 6 demonstrates the detection result interface, displaying the uploaded image alongside the AI-predicted ingredient label (e.g., Ginger) and a confidence score (e.g., 90%) to verify accuracy.

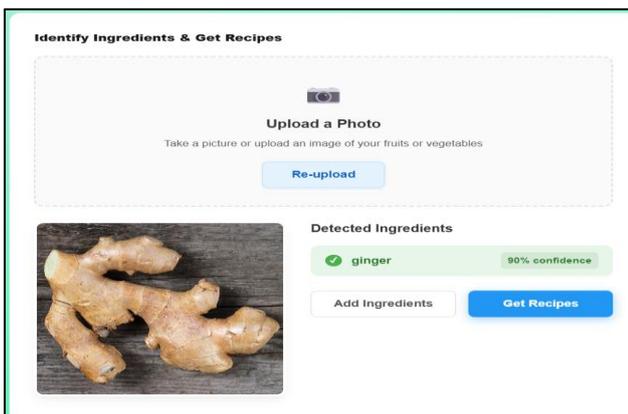


Fig. 6 detected ingredients after image upload.

Ingredient detection is a distinguishing capability of NutriMatch compared with existing web-based nutrition and recipe platforms. MyFitnessPal, PlateJoy, and Supercook do not provide ingredient detection from user images, meaning users must rely on manual input or pre-defined search to begin meal planning and tracking [8-10]. In contrast, NutriMatch supports browser-based image upload and automatic produce recognition, returning a predicted ingredient label (with a confidence score) that can be immediately used to drive recipe filtering and personalization.

D. Recipe Recommendations

Once the ingredients are confirmed, the system transitions to the Recipe Recommendation module. To

ensure nutritional balance, the system provides a comprehensive workflow where, following ingredient detection, users are allowed to manually select additional carbohydrate or protein source. This step ensures that the generated recipes consist of a complete and balanced meal. Fig. 7 presents the selection of Carbohydrate and Protein the user can add before generating the recipe.

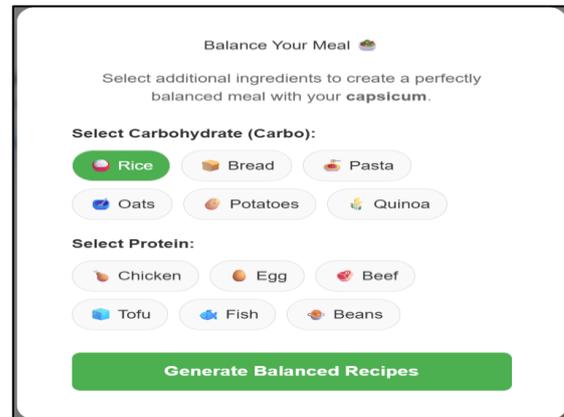


Fig. 7 Selection of Carbohydrate and Protein

Based on the detected produce, selection of additional nutrient and the user's pre-set dietary profiles, NutriMatch queries its database to generate a curated grid of recipe cards. Each card provides essential details, including the recipe title, total calorie count, and relevant cuisine tags. Fig. 8 presents the recipe grid, illustrating how users can view recommendations, bookmark recipes, or click the '+' button to instantly track the meal in their daily log.

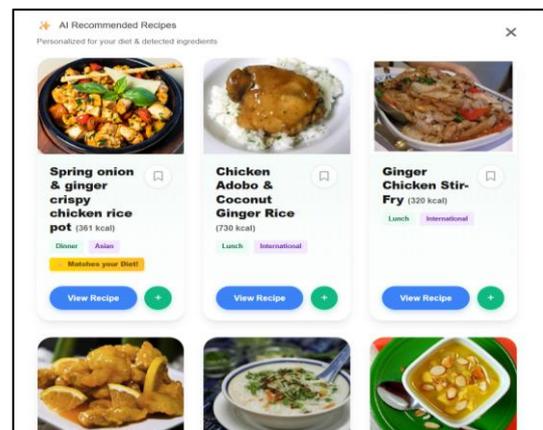


Fig. 8 Balanced recipe recommendations based on user ingredients.

E. Testing and Evaluation

The system underwent rigorous testing to validate its performance. The AI model achieved a high classification accuracy of 0.89 and an F1-score of 0.88 on the unseen test dataset, indicating reliable performance in distinguishing between different types of produce. Furthermore,

functional testing confirmed that all critical modules, including image uploading, API communication, and recipe filtering, are operated without errors.

The NutriMatch system's implementation of the MobileNetV2 architecture leverages inverted residuals and linear bottlenecks to optimize efficiency for web-based deployment, significantly reducing memory and computational operations while maintaining the high representational power required for ingredient classification [7]. These results are consistent with prior studies showing that deep learning models can remain robust under real-world variations (for example, lighting and background changes) in food-related recognition tasks [2].

Prior work has compared object detection models such as YOLOv5 and EfficientDet across food datasets, reporting that YOLOv5 can achieve better accuracy (mAP) and faster response time in those detection settings [6]. However, since NutriMatch focuses on lightweight ingredient classification for web-based deployment, this study adopts MobileNetV2 to balance accuracy and computational efficiency.

Furthermore, NutriMatch's focus on personalized meal recipes aligns with the identified need for tailored interventions based on gender-specific dietary patterns, such as the distinct food preferences and routine structures revealed through Principal Component Analysis (PCA) [5]. Finally, the successful functional testing of NutriMatch's API and image upload modules mirrors the development process of applications like MyDietCam, where rigorous lab and pilot testing are essential to prevent the crashing and lagging issues that frequently lead users to abandon digital dietary monitoring tools.

V. CONCLUSION

Future improvements for NutriMatch include extending the detection model to be able recognise multiple ingredients within a single image and upgrading the Spoonacular API plan to support higher request limits and richer nutritional data. A chatbot feature may be added to enhance user interaction, while conversion to a mobile application would improve accessibility. Additional enhancements include religion-based dietary filtering, integration of generative AI for more intelligent recipe recommendations, and the ability to estimate ingredient freshness and quantity for better serving suggestions.

NutriMatch demonstrates the effective use of artificial intelligence and web technologies to support healthier eating through automated ingredient detection and personalized recipe recommendations. The system reduces the effort required for meal planning, particularly for users with busy lifestyles. Despite limitations such as API restrictions and model capability, the system achieves

its objectives and shows strong potential for future expansion into a smart nutrition assistant.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHORS CONTRIBUTION STATEMENT

All authors contributed equally to this work.

DATA AVAILABILITY STATEMENT

There is no external or third-party data that support the findings of this study.

ETHICS STATEMENT

This study did not require ethical approval

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