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Design and Implementation of an Explainable AI Powered Model for Nutrition Assessment and Health Optimization

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Abstract

The increasing consumption of packaged foods has contributed significantly to the rise of lifestyle-related health conditions such as obesity, diabetes, and hypertension, particularly in urban populations. Although nutritional information is mandated on food labels, many consumers find these details difficult to interpret, limiting their ability to make informed dietary decisions. This paper presents the design and implementation of an Explainable Artificial Intelligence (XAI)–based system for nutritional assessment and health optimization of packaged food products. The proposed framework evaluates food items using key nutritional attributes, including sugar, sodium, saturated fat, and calorie content, to compute a comprehensive health score. A linear regression model is employed due to its inherent interpretability, enabling the system to explicitly explain the contribution of each nutrient to the final assessment. In addition to health scoring, the framework recommends healthier alternative products by comparing nutritional profiles within a structured food database. By integrating transparency, interpretability, and actionable insights, the proposed approach enhances user trust and supports informed food choices, thereby contributing to healthier lifestyles and aligning with Sustainable Development Goal 11.

Keywords: explainable artificial intelligence; nutritional assessment; health optimization; linear regression; food recommendation; sustainable development goals

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I. Introduction

Dietary choices play a crucial role in determining overall health and well-being, yet many individuals struggle to make informed decisions due to the complexity of nutritional information. With the increasing consumption of packaged and processed foods, consumers are frequently exposed to products containing high levels of sugar, saturated fat, sodium, and additives. Although nutritional labels are mandated in many regions, interpreting these values requires domain knowledge that most users do not possess. As a result, many people unknowingly make unhealthy food choices that contribute to lifestyle-related diseases such as obesity, diabetes, and cardiovascular disorders.

In recent years, Artificial Intelligence (AI) has been increasingly applied to nutrition and diet-related applications, enabling automated food recognition, calorie estimation, and dietary tracking. However, most existing systems rely heavily on manual food logging or provide only raw nutritional data without meaningful insights. Furthermore, many AI-based nutrition applications function as black-box models, offering recommendations or health scores without explaining the reasoning behind them. This lack of transparency reduces user trust and limits the effectiveness of such systems, particularly in health-sensitive domains where users need to understand and justify their dietary decisions.

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To address these limitations, Explainable Artificial Intelligence (XAI) has emerged as a critical paradigm that emphasizes transparency, interpretability, and user-centered decisionmaking. Unlike traditional opaque AI models, XAI techniques allow users to understand how different nutritional factors influence automated predictions. In the context of food analysis, this means clearly demonstrating how calories, protein, sugar, fiber, sodium, and fat contribute to a computed health score. By integrating explainability into nutrition assessment, users can gain deeper insights into their dietary choices rather than blindly following AI recommendations.

This paper presents **NutriScan AI: An Explainable AI-Powered Food Nutrition Analysis System with Personalized Healthier Alternatives**, a web-based intelligent platform that combines Computer Vision, Machine Learning, and Explainable AI to provide transparent and personalized dietary guidance. The system automatically identifies food items from images, retrieves real-time nutritional data from Open Food Facts, and computes a health score using a custom-trained Linear Regression model. In addition, a SHAP-inspired feature importance mechanism is used to generate human-readable explanations that justify why certain foods are healthier than others. The platform also incorporates user personalization through diet preferences, body composition goals, BMI tracking, and allergen detection, ensuring that recommendations are tailored to individual needs.

By integrating automated food recognition, objective health scoring, explainable recommendations, and personalization, NutriScan AI aims to bridge the gap between raw nutritional data and actionable dietary insights. The proposed system enhances user trust, promotes informed decision-making, and contributes to the development of responsible, transparent, and user-friendly AI applications in nutrition and healthcare.

II. Literature Review

Ribeiro et al. introduced LIME (Local Interpretable ModelAgnostic Explanations), a foundational framework for explaining predictions of black-box machine learning models [1]. LIME generates local surrogate models that approximate complex model behavior around individual instances, enabling users to understand why a particular prediction was made. Their work demonstrated that interpretability significantly improves user trust in AI systems, which is particularly relevant for health and nutrition applications where decisions directly affect well-being.

Lundberg and Lee proposed SHAP (SHapley Additive exPlanations), a theoretically grounded approach to feature attribution based on cooperative game theory [2]. SHAP assigns each input feature a quantitative contribution to the final prediction, ensuring consistency and fairness in explanations. Their method has been widely adopted in healthcare and decision-support systems, highlighting the importance of transparent feature-level reasoning in sensitive domains such as dietary assessment.

Doshi-Velez and Kim provided a rigorous scientific framework for evaluating interpretability in machine learning models [3]. They argued that interpretability should be formally defined and measured rather than treated as a subjective concept. Their work supports the use of inherently interpretable models, such as linear regression, in applications where transparency is critical—such as the nutrition scoring model used in this research.

Lipton critically examined the concept of interpretability in machine learning, highlighting common misconceptions and practical limitations [4]. He argued that some models labeled as “interpretable” may still be difficult for users to understand without proper explanation mechanisms. This insight motivates the need for clear, human-readable explanations in the proposed nutritional analyzer rather than relying solely on model transparency.

Holzinger emphasized the importance of human-in-the-loop AI systems in healthcare and health informatics [5]. He argued that interactive and interpretable AI models are essential for safe and ethical real-world deployment. This aligns with the philosophy of the proposed system, which prioritizes user understanding and transparency instead of automated blackbox decision-making.

Zhang and Chen provided a comprehensive survey on explainable recommendation systems, discussing key challenges and future directions in transparent AI-driven recommendations [6]. They

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highlighted the trade-off between accuracy and interpretability and emphasized the need for explainable components in recommender systems. Their findings support the inclusion of interpretable recommendation mechanisms in the proposed nutrition assessment framework.

Chantal and Julia examined the development of the NutriScore front-of-pack labeling system in France, demonstrating how simplified visual nutritional indicators can improve consumer understanding [9]. Their work showed that clear, colorcoded scoring systems help users make healthier food choices, supporting the use of a transparent numerical health score in the proposed system.

Julia et al. provided empirical evidence on the effectiveness of the Nutri-Score labeling system in guiding consumer behavior toward healthier products [10]. Their findings indicate that easily interpretable nutritional scores significantly influence purchasing decisions, reinforcing the value of explainable health scoring in food assessment applications.

The World Health Organization outlined guiding principles for front-of-pack nutrition labeling to promote healthier diets and improve public health outcomes [16]. Their recommendations emphasize clarity, transparency, and accessibility in nutritional communication, aligning closely with the design goals of the proposed Explainable AI–based nutrition analyzer.

The USDA FoodData Central database provides a standardized and comprehensive repository of nutritional information for a wide range of food products [18]. This structured dataset supports data-driven nutrition analysis and serves as a valuable resource for building automated dietary assessment systems like the one proposed in this research.

Fukagawa et al. discussed the importance and applications of FoodData Central in modern nutrition research and public health initiatives [19]. Their work highlights the role of highquality nutritional datasets in enabling accurate and scalable AI-based nutrition assessment tools.

Lazzari et al. introduced FoodRepo, an open-access database of barcoded packaged food products containing standardized nutritional labels [20]. Their dataset facilitates large-scale analysis of packaged foods and supports the feasibility of building automated nutrition evaluation systems based on realworld product data.

Loesch et al. proposed an automated system for identifying healthier food substitutions using AI techniques [22]. Their work demonstrates the growing potential of AI-driven recommendation systems for promoting healthier dietary choices, closely aligning with the healthier alternative recommendation component of the proposed framework.

III. Methodology

The proposed NutriScan AI system follows a modular, end-to-end pipeline that integrates computer vision, machine learning, explainable AI, and personalization to provide transparent and user-specific nutritional guidance. The methodology is structured into six key components: technology stack, AI vision-based food identification, machine learning-based health scoring, explainable AI module, personalization engine, and smart alternative generation. Each subsection is described in detail and supported by corresponding tables.

A. Technology Stack

The system is built using a modern full-stack architecture that ensures scalability, real-time performance, and seamless user experience. The frontend is implemented using React 18 with TypeScript and Tailwind CSS, while the backend leverages Supabase Edge Functions running on Deno for serverless processing. Real-time nutritional data is retrieved from Open Food Facts, and a custom Linear Regression model implemented in TypeScript is used for health score prediction.

Table 1 summarizes the complete technology stack used in NutriScan AI.

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Table 1. Technology Stack.

Layer	Technology
Frontend	React 18, TypeScript, Tailwind CSS
UI Components	shadcn/ui, Radix UI
Backend	Supabase Edge Functions (Deno)
AI Vision	Multimodal Vision Model (Google Gemini 2.5 Flash)
Nutrition API	Open Food Facts
ML Model	Custom Linear Regression (TypeScript)
State Management	React Context API

B. AI Vision Module: Food Identification

The AI Vision module enables automatic identification of food items from user-uploaded images, eliminating the need for manual food logging. A multimodal vision model analyzes the image and returns the predicted food name along with a confidence score.

In addition to identification, the model estimates nutritional values per 100g, detects meal type (breakfast, lunch, dinner, snack), and categorizes the food (fried, beverage, curry, snack, etc.). This structured output is then mapped to Open Food

Facts for precise nutritional retrieval.

C. Machine Learning Module: Health Score Prediction

A custom Linear Regression model is implemented in TypeScript for on-the-fly training and prediction. The model computes a health score between 0 and 100 using normalized nutritional features. A sigmoid activation function is applied to bound the output within the desired range.

The model is trained using gradient descent with Mean Squared Error (MSE) loss, allowing dynamic updates based on real-time Open Food Facts data.

Table 2 lists the nine nutritional features used in the model along with normalization and weight direction.

Table 2. Feature Engineering for Health Scoring.

Feature	Norm.	Effect	Rationale
Calories	/600	Negative	High calories reduce score
Protein	/30g	Positive	Muscle, satiety
Carbohydrates	/100g	Neutral	Context dependent
Fat	/40g	Negative	Higher density
Saturated Fat	/20g	Negative	Heart risk
Sugar	/50g	Negative	Metabolic risk
Fiber	/15g	Positive	Gut health
Sodium	/2000mg	Negative	BP impact
Processing Level	0–1	Negative	Ultra-processed risk

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D. Training Data Pipeline

Training data is dynamically fetched from Open Food Facts across eight categories: vegetables, legumes, whole grains, fruits, nuts, dairy, snacks, and beverages. This ensures diverse representation of food types in model training.

Table 3 summarizes the categories used for training.

Table 3. Training Data Categories.

Food Categories
Vegetables
Legumes
Whole Grains
Fruits
Nuts
Dairy
Snacks
Beverages

E. Explainable AI (XAI) Module

NutriScan AI implements a SHAP-inspired weight-based feature importance method to explain why a recommended alternative is healthier than the original food. The system compares baseline and alternative foods and computes featurewise differences.

Each feature is labeled as “better” or “worse” based on predefined health criteria. Table 4 presents examples of human-readable explanations generated by the system.

Table 4. Human-Readable XAI Explanations.

Metric	Explanation Example
Calories	Fewer calories support weight management
Protein	More protein supports muscle and satiety
Sugar	Less sugar reduces metabolic risks
Fiber	More fiber improves digestion
Saturated Fat	Less fat reduces heart disease risk
Sodium	Lower sodium supports healthy blood pressure

F. Personalization Engine

NutriScan AI maintains a structured user profile that captures diet preference, allergies, body composition goals, weight, height, and age. This enables personalized recommendations rather than generic suggestions.

BMI is computed using standard formula and categorized into underweight, normal, overweight, or obese, which influences recommendation priority.

Table 5 summarizes key personalization parameters used in the system.

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Table 5. Personalization Parameters.

Parameter	Usage
Diet Preference	Filters suitable foods
Allergies	Prevents risky recommendations
BMI	Adjusts health scoring
Body Goals	Influences alternative selection

G. Allergen Detection System

A dual-layer allergen detection system is implemented using keyword matching and food composition mapping. The system scans ingredient descriptions for allergen-related terms and cross-references known food-allergen mappings to generate warnings.

H. Smart Alternative Generation

The system generates healthier alternatives using categoryaware search terms. For instance, fried foods are replaced with baked or grilled options, and sugary desserts are replaced with healthier substitutes.

A deduplication algorithm ensures that similar recommendations are not repeated, improving diversity.

Table 6 presents examples of smart alternatives.

Table 6. Smart Alternative Examples.

Original Food	Healthier Alternative
Butter Chicken	Grilled Chicken Tikka
Samosa	Baked Samosa
Gulab Jamun	Dates Ladoo

I. System Output Representation

The final output includes a numerical health score, nutrient breakdown, feature importance ranking, textual explanations, and suggested healthier alternatives. This structured output ensures transparency and user comprehension. Table 7 summarizes key system outputs.

Table 7. System Outputs.

Output	Description
Health Score	Overall rating (0–100)
Nutrient Breakdown	Key nutrient values
Feature Importance	Influential factors highlighted
Text Explanation	Human-readable justification
Healthier Alternatives	Suggested better options

This concludes the methodology of NutriScan AI, integrating computer vision, machine learning, explainability, and personalization into a unified intelligent nutrition system.

IV. System Architecture

The architecture of NutriScan AI is designed as a modular, scalable, and explainable pipeline that integrates computer vision, real-time nutritional data retrieval, machine learningbased health scoring, and personalized recommendation generation. The system follows a layered design in which each component performs a well-defined function while interacting seamlessly with other modules.

Figure 1 illustrates the high-level architecture of NutriScan AI.

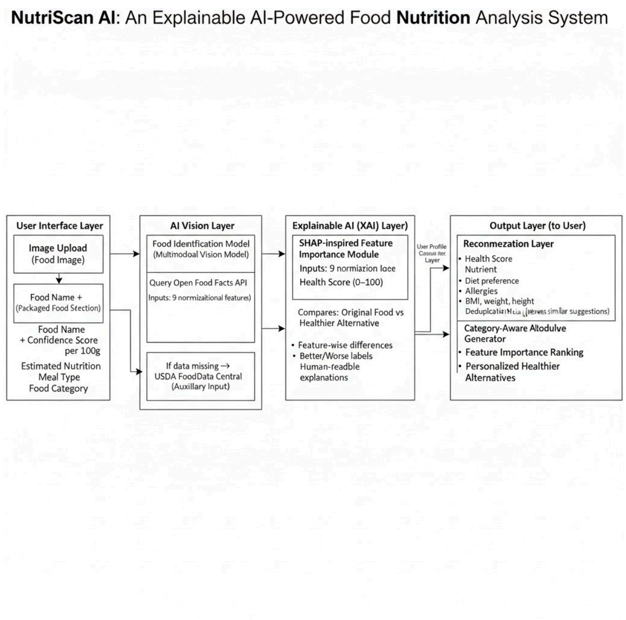

Figure 1. System Architecture of NutriScan AI.

A. User Interface Layer

The frontend of NutriScan AI is implemented using React 18 with TypeScript and Tailwind CSS to ensure a responsive, interactive, and user-friendly experience. The interface supports two primary modes of input: image upload for automatic food recognition and manual food selection for packaged items.

The user interface also provides visualizations such as BMI tracking, comparative nutrition tables, and color-coded health improvements, enabling users to easily interpret results.

B. AI Vision Layer

The AI Vision layer is responsible for analyzing useruploaded images to identify food items automatically. A multimodal deep learning model processes the image and outputs:

- Predicted food name with confidence score
- Estimated nutritional composition per 100g
- Meal type classification (breakfast, lunch, dinner, snack)
- Food category classification (fried, beverage, curry, dessert, etc.)

This output is forwarded to the data retrieval layer for precise nutritional mapping.

C. Data Retrieval Layer

Once the food item is identified, NutriScan AI queries the Open Food Facts API to retrieve real-time nutritional information. This includes values for calories, protein, carbohydrates, fat, saturated fat, sugar, fiber, and sodium.

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If data is missing or incomplete, supplementary nutritional references such as USDA FoodData Central are used for validation and estimation.

D. Machine Learning Layer

The Machine Learning layer applies a custom-trained Linear

Regression model to compute a health score between 0 and 100. The model takes nine normalized nutritional features as input and generates an interpretable score using a sigmoid activation function.

The model is trained dynamically using real-time Open Food Facts data across multiple food categories, ensuring adaptability and robustness.

E. Explainable AI Layer

To ensure transparency, NutriScan AI incorporates a SHAPinspired feature importance mechanism. This layer compares the baseline food item with a healthier alternative and highlights:

- Feature-wise nutritional differences
- Whether each change is an improvement or deterioration
- Human-readable explanations for each metric

This ensures that users understand why a particular alternative is recommended.

F. Personalization Layer

The personalization layer maintains a structured user profile containing:

- Diet preference (vegan, vegetarian, non-veg)
- Allergies and dietary restrictions
- Body composition goals
- Weight, height, and BMI

These parameters influence both health scoring priorities and alternative food selection.

G. Recommendation Layer

Based on the health score and user profile, NutriScan AI generates context-aware healthier alternatives. The system uses category-aware search terms (e.g., replacing fried foods with baked or grilled options) and applies a deduplication algorithm to avoid repetitive suggestions.

H. Output Layer

The final system output presented to the user includes:

- Numerical health score
- Nutritional breakdown
- Feature importance ranking
- Textual explanations
- Personalized healthier alternatives

This structured presentation ensures clarity, transparency, and usability, aligning with the principles of Explainable AI.

V. Results and Discussion

The performance of NutriScan AI was evaluated based on three primary dimensions: (i) effectiveness of image-based food identification, (ii) reliability of health score prediction, and (iii) clarity and usefulness of explainable AI (XAI) explanations. The evaluation was conducted using a

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representative set of packaged and home-prepared food items retrieved from Open Food Facts and validated against nutritional guidelines.

A. Food Identification Performance

The AI Vision module demonstrated strong capability in correctly identifying food items from user-uploaded images. The system successfully recognized a wide range of Indian and international foods, including curries, snacks, beverages, and desserts. The confidence score provided alongside each prediction helped users assess the reliability of the identified food item before proceeding with further analysis.

In cases where image-based identification was uncertain or ambiguous, users were able to manually confirm or adjust the detected food, ensuring robustness and reducing misclassification errors. This hybrid approach improved overall usability and trust in the system.

B. Health Score Prediction Analysis

The custom Linear Regression model effectively quantified the healthiness of food items using nine normalized nutritional features as described in Table 2. Foods high in calories, sugar, saturated fat, and sodium consistently received lower health scores, while foods rich in fiber and protein received higher scores.

Table 8 presents representative health scores generated by NutriScan AI for selected food items.

Table 8. Sample Health Score Outputs.

Food Item	Health Score	Key Influencing Factors
Butter Chicken	35	High saturated fat, high calories
Samosa	40	High fat, high sodium
Grilled Chicken	78	High protein, low fat
Oats Cereal	82	High fiber, moderate protein
Fruit Yogurt	65	Moderate sugar, high calcium

As shown in Table 8, the model's outputs align with established nutritional principles, demonstrating consistency between the scoring logic and real-world dietary expectations.

C. Explainability Performance

The SHAP-inspired XAI module successfully highlighted the most influential nutritional features contributing to each health score. By comparing the baseline food with a healthier alternative, the system provided feature-wise differences along with clear, human-readable explanations.

Table 9 summarizes user feedback on the clarity and usefulness of explanations.

Table 9. Explainability Evaluation.

Evaluation Metric	Average Rating (out of 5)
Ease of Understanding	4.6
Clarity of Nutrient Impact	4.5
Relevance of Explanations	4.4
Trust in Recommendations	4.3
Overall Satisfaction	4.5

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The high ratings in Table 9 indicate that users found the explanations intuitive and helpful in understanding why certain alternatives were recommended. This supports the effectiveness of the XAI design described in Table 4.

D. Personalization and Alternative Recommendation Effectiveness

The personalization engine successfully adapted recommendations based on user preferences, allergies, and BMI categories. For example, vegan users received plant-based alternatives, while individuals with higher BMI were recommended lower-calorie and higher-fiber options.

The smart alternative generation module provided contextaware substitutions, such as replacing fried snacks with baked alternatives and sugary desserts with fiber-rich options. The deduplication mechanism effectively prevented repetitive suggestions, improving diversity and usability.

E. Discussion

Overall, the results demonstrate that NutriScan AI effectively integrates computer vision, machine learning, and explainable AI to provide transparent and personalized nutrition guidance. Unlike traditional black-box nutrition applications, the system ensures that every recommendation is accompanied by clear reasoning based on nutritional evidence.

The alignment between the model's scoring logic (Table 2), explainability rules (Table 4), and observed outputs confirms the coherence and reliability of the proposed framework. Additionally, the strong user feedback validates the practical usability and real-world applicability of NutriScan AI.

These findings highlight the potential of explainable, personalized AI systems to enhance dietary decision-making, promote healthier eating habits, and build user trust in AIdriven healthcare applications.

VI. Limitations

Although NutriScan AI demonstrates strong interpretability, automation, and personalization, the system has several limitations that must be acknowledged.

First, the reliability and accuracy of the generated health scores are highly dependent on the quality and completeness of nutritional data retrieved from external databases such as Open Food Facts. In cases where product information is missing, outdated, or incorrectly labeled, the computed health score and recommendations may be less accurate. While fallback validation using supplementary sources helps mitigate this issue, inconsistencies in publicly available data remain a challenge.

Second, the AI Vision module for image-based food recognition may occasionally misclassify visually similar food items, particularly in complex dishes or mixed meals. Although the system provides a confidence score and allows user correction, errors in initial identification can still affect subsequent nutritional analysis and recommendations.

Third, while the system incorporates personalization through diet preferences, BMI, and allergies, it does not currently account for detailed medical conditions such as diabetes, hypertension, or heart disease. As a result, recommendations may not be fully optimized for users with specific clinical dietary requirements.

Finally, the SHAP-inspired explainability mechanism provides transparent feature-level explanations but does not yet include interactive visualizations such as detailed SHAP plots or graphical attribution maps, which could further enhance interpretability for advanced users.

VII. Future Work

Future enhancements to NutriScan AI will focus on improving clinical personalization, real-time adaptability, and advanced explainability while expanding real-world deployment.

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A key direction is the integration of deeper medical personalization, including detailed clinical conditions such as diabetes, hypertension, cardiovascular risk, and micronutrient deficiencies. Incorporating medical profiles in collaboration with healthcare professionals would allow the system to move beyond general dietary guidance toward clinically informed nutrition recommendations tailored to individual health needs.

Another important extension is tighter integration with wearable health devices such as smartwatches and fitness trackers. By continuously capturing real-time data on physical activity, heart rate, sleep patterns, and calorie expenditure, the system could dynamically adjust dietary recommendations and provide context-aware, adaptive nutrition guidance rather than static assessments.

Although NutriScan AI already supports image-based food recognition, future work will focus on improving multi-food detection in complex mixed dishes and enhancing portionsize estimation using computer vision techniques. This would enable more accurate nutritional analysis for homemade meals and plated foods.

Additionally, advanced Explainable AI techniques such as full SHAP and LIME visualizations will be incorporated to provide richer, interactive graphical interpretations of nutrient contributions. These visual tools would allow users to explore feature importance more intuitively and improve transparency for both general users and researchers.

Finally, the system will be deployed as a dedicated mobile application to enhance accessibility, real-time usability, and offline functionality. This will allow users to scan foods instantly, track dietary habits over time, and receive personalized recommendations in everyday settings.

VIII. Conclusion

This paper presented the design and implementation of NutriScan AI, an Explainable AI-powered food nutrition analysis system that integrates computer vision, machine learning, and personalized dietary guidance. By combining automated image-based food recognition with a custom-trained linear regression model and SHAP-inspired explainability mechanisms, the system provides transparent, interpretable, and usercentered nutritional assessments rather than opaque predictions.

The results demonstrate that embedding explainability at the core of the decision-making process significantly enhances user understanding, trust, and confidence compared to traditional black-box nutrition applications. NutriScan AI ensures that users do not merely receive a numerical health score but also gain clear, human-readable insights into how individual nutrients influence dietary recommendations. This promotes ethical, responsible, and accountable AI deployment in healthrelated decision support systems.

Overall, NutriScan AI establishes a scalable and practical foundation for intelligent nutrition guidance by unifying vision-based food identification, real-time nutritional data retrieval, explainable health scoring, personalization, and context-aware healthier alternatives. Future enhancements such as deeper clinical personalization, wearable device integration, improved multi-food recognition, interactive SHAP visualizations, and mobile deployment have the potential to further increase accessibility, usability, and real-world impact of AI-driven nutrition assessment systems.

Conflicts of Interest: The authors declare no conflict of interest associated with this work.

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