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Nutralyze: An AI-Driven Multimodal System for Automated Nutrition Analysis, Ingredient Risk Detection, and Food Label Analysis

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Abstract: *Automated food analysis systems are becoming in-creasingly important for supporting healthy dietary habits and informed nutritional decision-making. However, many existing so-lutions rely on extensive manual input, limited food databases, or single-modality processing, which restrict their practical usability. This paper presents Nutralyze, a full-stack multimodal nutrition analysis platform that integrates AI-based food recognition, ingredient safety assessment, and personalized dietary guidance. The system employs a dual-stage Large Language Model (LLM) pipeline in which the Llama-4-Scout vision model identifies food items and estimates portion sizes from food images, while the Llama-3.1-70B model estimates nutritional composition for the detected serving. For packaged food products, Nutralyze com-bines barcode-based product retrieval using the Open Food Facts database with Optical Character Recognition (OCR) through Tesseract for ingredient extraction. The extracted ingredients are normalized and analyzed using AI-driven processing and a curated risk-scored database aligned with regulatory standards such as FSSAI, FDA, and EU guidelines. The platform further generates personalized diet plans by considering user health profiles, dietary restrictions, nutritional requirements, and real-time intake tracking. Nutralyze is deployed as a responsive web application supporting real-time meal logging, progress monitoring, and a multilingual AI nutrition chatbot in English, Hindi, and Marathi. Experimental evaluation demonstrates a caloric estimation error (MAPE) of 10.07% and an OCR-based ingredient parsing accuracy (F1-score) of 95.98%, indicating improved flexibility, usability, and accuracy compared with traditional CNN-based approaches.*

Keywords: Large Language Models (LLMs), Multimodal Food Recognition, Nutrition Analysis, OCR, Ingredient Safety Analysis, Personalized Diet Planning, Food Safety, Dietary Guid-ance, Health Monitoring

I. INTRODUCTION

Nutrition plays a crucial role in maintaining overall health and preventing lifestyle-related diseases such as obesity, dia-betes, and cardiovascular disorders. Studies have shown that proper dietary habits and nutritional interventions can signifi-cantly improve health outcomes and reduce the risk of chronic diseases [1]. However, monitoring daily food consumption and accurately assessing nutritional intake remain challenging tasks due to the complexity of food composition and the effort required for manual tracking.

Recent advancements in computer vision and artificial in-telligence have enabled the development of automated food recognition and dietary assessment systems. Deep learning techniques have demonstrated promising results in recognizing food items from images captured in real-world environments [2], [13]. Furthermore, large-scale food datasets and deep learning-based frameworks have facilitated the development of systems capable of estimating nutritional values directly from food images [4], [6]. Convolutional Neural Networks (CNNs), Inception-based architectures, and multi-scale feature extraction techniques have been widely adopted to improve food classification performance and visual feature learning [5], [18].

Several studies have explored image-based food classifica-tion and volume estimation for dietary assessment, highlight-ing the importance of accurate food recognition in nutritional analysis [6]. Recent approaches have incorporated RGB-D information and depth sensing technologies to improve portion size estimation and calorie prediction [7], [8]. Additionally, transformer-based architectures have demonstrated strong ca-pabilities in capturing global contextual information from images [9], [12].

Despite significant progress in food recognition and nutri-tion estimation, many existing systems focus on individual tasks rather than providing a unified solution for comprehen-sive dietary management. Most approaches lack the capability to simultaneously analyze food images, evaluate ingredient safety, and generate personalized dietary recommendations [17], [20].

To address these limitations, this paper presents Nutralyze, an AI-driven nutrition analysis platform that integrates food recognition, nutritional estimation, ingredient risk detection, and personalized dietary guidance. The proposed system lever-ages artificial intelligence techniques, OCR-based ingredient extraction, and nutritional databases to provide users with meaningful dietary insights.

II. LITERATURE SURVEY

Recent advancements in artificial intelligence and com-puter vision have significantly improved food recognition and nutrition analysis systems. Fakhrou et al. [2] and Szegedy et al. [3] developed deep learning-based food recognition models capable of identifying food items in complex real-world scenarios. The Nutrition5K-related research and large-scale deep learning approaches support automated nutritional understanding and dietary assessment [4], [6].

Several studies have focused on nutrition estimation us-ing food images. Lo et al. [6] reviewed image-based food classification and volume estimation techniques, while Shao et al. [9] and Vinod et al. [8] improved nutritional estima-tion using RGB-D and depth-based information. Transformer-based architectures such as Vision Transformer and Swin Transformer have also demonstrated strong performance in image understanding and food analysis tasks [7], [10].

Recent research has also explored advanced deep learn-ing models such as CNN-based architectures and attention mechanisms to improve food image classification accuracy and feature extraction capabilities [13], [16]. DeepFood and other dietary assessment systems have shown promising re-sults in automatically analyzing food images and generating nutritional insights [13], [17]. These developments highlight the growing role of AI in supporting intelligent healthcare and nutrition management applications.

Despite these advancements, most existing systems con-centrate on food recognition or calorie estimation alone. They provide limited support for ingredient safety assessment and personalized dietary recommendations. To address these limitations, Nutralyze integrates food recognition, nutritional estimation, ingredient risk analysis, and personalized diet planning within a single intelligent platform.

III. PROPOSED METHODOLOGY

The planned system will be covering by a four-part division of task to it. Every module plays a specific role according to the workflow, ranging from the food items analysis to personalized dietary recommendations generation. This type of modular approach promotes efficient data flow as well as accuracy and maintainability. Below are detailed the four modules:

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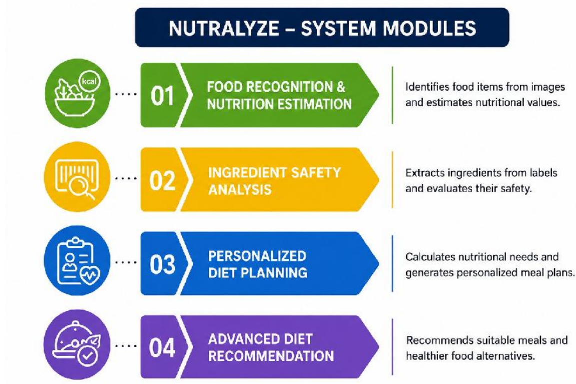

Fig. 1: System Modules.

A. Module 1: Food Recognition and Nutrition Estimation

This module is responsible for identifying food items and estimating their nutritional content from images uploaded by users. Initially, the uploaded image undergoes preprocessing operations such as resizing, normalization, and quality en-hancement to improve image clarity and ensure accurate anal-ysis. The processed image is then analyzed using the Llama-4-Scout Vision Model, which extracts meaningful visual features and recognizes food items from different cuisines and meal categories.

The input image can be represented as:

$$I(x, y)$$

where x and y denote the pixel coordinates of the image. The visual feature extraction process is represented as:

$$F = \phi(I)$$

where ϕ denotes the feature extraction function and F represents the extracted feature vector. These features capture important characteristics of the food item, including shape, texture, color, and portion information.

The extracted features are used to identify the food category. The probability of a food item belonging to a particular class is computed using the Softmax function:

$$P(y = k|z) = \frac{e^{z_k}}{\sum_{j=1}^{C} e^{z_j}}$$

where zk represents the score associated with class k and C denotes the total number of food categories.

After successful food recognition, the identified food infor-mation is supplied to the Llama-3.1-70B model for nutritional estimation. The nutritional profile generated by the system is represented as:

$$N = [Cal, Pro, Carb, Fat, Sug, Fib]$$

where Cal, Pro, Carb, Fat, Sug, and Fib represent calo-ries, proteins, carbohydrates, fats, sugar, and fiber respectively.

The overall nutritional value can be expressed as:

$$T_N = \sum_{i=1}^{n} w_i n_i$$

where ni denotes an individual nutritional component and wi represents its corresponding weight factor.

Based on the identified food item and estimated portion size, the system generates detailed nutritional information including calories, proteins, fats, carbohydrates, sugar, fiber, vitamins, and minerals whenever available. The generated nutritional data is stored in the database and used for dietary monitoring, calorie tracking, and personalized recommendation generation. This module enables users to obtain accurate nutritional in-sights directly from food images without requiring manual food logging, making nutrition assessment faster, more con-venient, and user-friendly.

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B. Module 2: Ingredient Safety Analysis

This module evaluates the safety of packaged food products by analyzing ingredient information obtained through barcode scanning or ingredient label images. When a barcode is scanned, product details are retrieved from the Open Food Facts database. If product information is unavailable, Tesseract OCR is used to extract textual information from the uploaded label image. The extracted text is then cleaned, standardized, and processed to obtain a structured list of ingredients.

The OCR extraction process can be represented as:

$$T = OCR(Il)$$

where Il denotes the label image and T represents the extracted textual information.

The ingredient list is represented as:

$$G = \{g1, g2, g3, . . . , gn\}$$

where each gi corresponds to an individual ingredient identified from the product label.

The extracted ingredients are processed using the Llama-3.1-8B Ingredient Parser, which normalizes ingredient names and removes inconsistencies. Each ingredient is compared against a curated risk database containing information about preservatives, artificial sweeteners, food colorants, additives, and other food compounds.

A risk score is assigned to every ingredient according to its potential health impact:

$$R_i = \begin{cases} 0, & \text{Safe Ingredient} \\ 1, & \text{Moderate Risk Ingredient} \\ 2, & \text{High Risk Ingredient} \end{cases}$$

The overall product risk score is calculated as:

$$PRS = \frac{1}{n}\sum_{i=1}^{n} R_i$$

where n denotes the total number of ingredients present in the product.

Based on the calculated risk score, the safety level of the product is determined as:

$$Safety = \begin{cases} Low, & PRS < 0.5 \\ Moderate, & 0.5 \le PRS < 1.5 \\ High, & PRS \ge 1.5 \end{cases}$$

To improve reliability, the identified ingredients are further validated using information collected from recognized food safety sources and ingredient databases. The system performs frequency analysis and evaluates the occurrence of risky ingre-dients within the product composition. Ingredients classified as harmful or potentially harmful are highlighted, while safe ingredients remain unmarked.

The final output consists of an ingredient safety report containing identified ingredients, risk levels, safety warnings, and consumption recommendations. This module enables users to quickly recognize potentially harmful food components and make informed dietary decisions while purchasing packaged food products.

C. Module 3: Personalized Diet Planning

The Personalized Diet Planning module generates cus-tomized dietary recommendations based on the user's health profile, nutritional requirements, and wellness goals. The mod-ule utilizes information such as age, gender, height, weight, ac-tivity level, dietary preferences, and nutritional data generated from the Food Recognition and Nutrition Estimation module. By combining these factors, the system creates personalized meal plans that support healthy eating habits and long-term health management.

The user profile is represented as:

$$U = [Age, Gender, Height, Weight, Activity, Goal]$$

where each parameter contributes to determining the user's nutritional requirements and dietary objectives.

To evaluate the user's physical condition, Body Mass Index (BMI) is calculated using:

$$BMI = \frac{W}{H^2}$$

where W represents body weight in kilograms and H represents height in meters.
The Basal Metabolic Rate (BMR), which represents the minimum amount of energy required by the body at rest, is calculated using the Mifflin-St Jeor equation.
For males:

$$BMR = 10W + 6.25H - 5A + 5$$

For females:

$$BMR = 10W + 6.25H - 5A - 161$$

where W denotes weight in kilograms, H denotes height in centimeters, and A denotes age in years.
The Total Daily Energy Expenditure (TDEE) is calculated as:

$$TDEE = BMR \times AF$$

where AF is the activity factor corresponding to the user's lifestyle.
The generated nutritional requirements are represented as:

$$R = [Cal, Pro, Carb, Fat, Fib]$$

where Cal, Pro, Carb, Fat, and Fib represent the daily requirements of calories, proteins, carbohydrates, fats, and fiber respectively.
Based on the calculated requirements, the Llama-3.3-70B model generates a personalized meal plan represented as:

$$D = [B, L, DN, S]$$

where:
• B =Breakfast
• L =Lunch
• DN =Dinner
• S =Snacks
To ensure nutritional balance, the recommendation system minimizes the difference between required and recommended nutrient values:

$$E = \sum_{i=1}^{n} |R_i - A_i|$$

where Ri represents the required nutrient value and Ai represents the nutrient value provided by the recommended meals.
The generated meal plans are dynamically adjusted ac-cording to the user's goals such as weight loss, weight gain, muscle development, or healthy maintenance. Dietary restrictions, allergies, and food preferences are also considered while generating recommendations. The final output consists of a personalized diet plan along with nutritional guidance, helping users maintain balanced nutrition and achieve their health objectives effectively.

D. Module 4: Advanced Diet Recommendation

The Advanced Diet Recommendation module provides per-sonalized meal suggestions based on the nutritional require-ments, dietary preferences, and health goals of the user. The module utilizes information generated from the Food Recogni-tion and Nutrition Estimation module, Ingredient Safety Anal-ysis module, and user health profile to recommend balanced and practical meal plans.
The recommendation process considers multiple factors in-cluding calorie requirements, nutrient intake, food preferences, allergies, lifestyle habits, and ingredient availability. These factors are represented as a feature vector:

$$F = [f1, f2, f3, \ldots, fn]$$

where each fi corresponds to a nutritional, behavioral, or preference-related attribute of the user.
The suitability score of a recommended meal is calculated as:

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$$S = \alpha 1N + \alpha 2H + \alpha 3P$$

where:

- N =Nutritional adequacy score
- H =Health compatibility score
- P =Preference matching score and

$$\alpha 1 + \alpha 2 + \alpha 3 = 1$$

The generated meal plans are filtered according to dietary restrictions such as vegetarian diets, allergies, and specific medical requirements. Meals that satisfy user constraints and nutritional goals receive higher recommendation scores.

The daily nutritional requirement is represented as:

$$R = [Cal, Pro, Carb, Fat, Fib]$$

where Cal, Pro, Carb, Fat, and Fib represent calories, proteins, carbohydrates, fats, and fiber respectively.

The final meal plan is generated as:

$$D = [B, L, DN, S]$$

where B, L, DN , and S denote breakfast, lunch, dinner, and snacks respectively.

The module continuously adapts recommendations accord-ing to user feedback, dietary habits, and nutritional progress. By combining nutritional analysis, ingredient safety evalu-ation, and user preferences, the system provides practical and personalized dietary guidance for maintaining a healthy lifestyle.

E. Web Application for Deployment

To demonstrate the practical implementation of the proposed Nutralyze system, a web-based application was developed that integrates food recognition, ingredient safety analysis, and per-sonalized diet planning into a single platform. The application allows users to upload food images, scan product barcodes, or analyze food labels to obtain nutritional information and ingredient details. Advanced AI models process the inputs and provide real-time results, including calorie estimates, nutrient composition, ingredient identification, and safety assessments. The user-friendly interface enables quick access to food-related information and supports informed dietary decision-making.

The application also provides personalized health and nutri-tion support through an interactive dashboard. Users can create health profiles by entering information such as age, gender, height, weight, and activity level. Based on these parameters, the system calculates nutritional requirements and generates customized meal recommendations aligned with individual health goals. Historical records, nutrition reports, and dietary recommendations are securely stored and managed, allowing users to monitor their progress over time. The deployed web application demonstrates the effectiveness of Nutralyze as a practical and intelligent solution for nutrition management, food safety evaluation, and healthy lifestyle guidance.

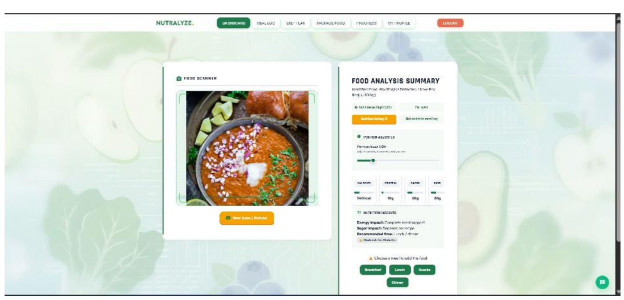

Fig. 2: Food Image Upload and Recognition

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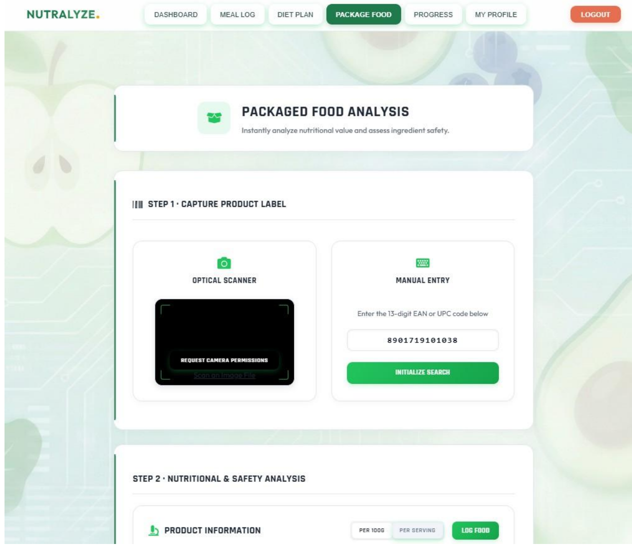

Fig. 3: Barcode and OCR Scanner Interface

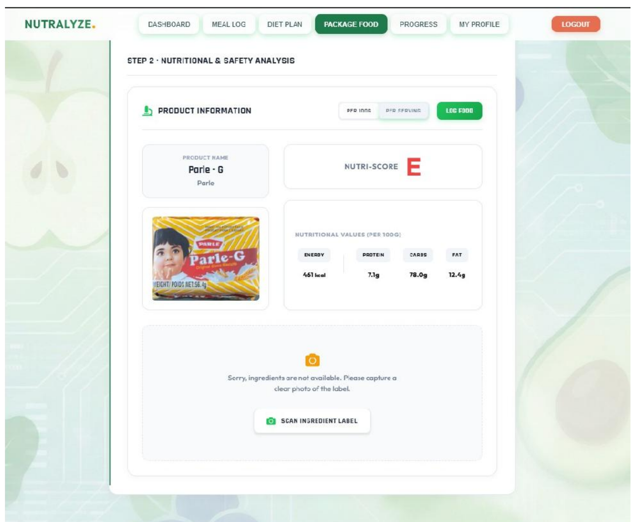

Fig. 4: Nutritional and Ingredient Safety Analysis

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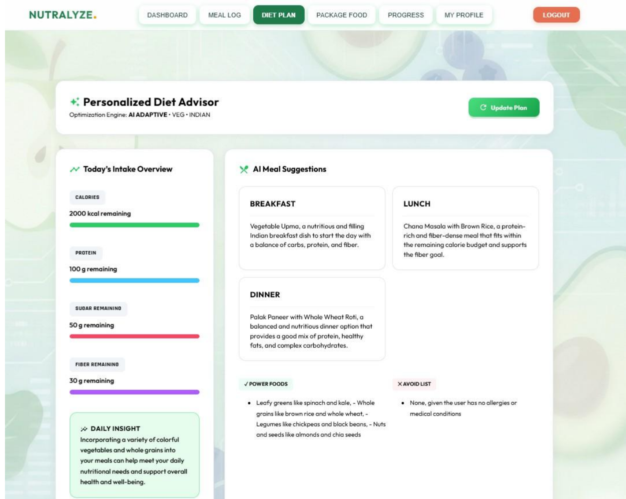

Fig. 5: Diet Recommendation Page

IV. SYSTEM DESIGN AND ARCHITECTURE

The Nutralyze system is designed as an intelligent and modular nutrition analysis platform that combines artificial intelligence, computer vision, OCR technology, and nutritional databases to provide comprehensive dietary insights. Users interact with the system through a web-based interface where they can upload food images, scan product barcodes, analyze ingredient labels, and manage their health profiles. The archi-tecture is organized into three main modules: Food Recogni-tion and Nutrition Estimation, Ingredient Safety Analysis, and Personalized Diet Planning.

The Food Recognition and Nutrition Estimation module analyzes uploaded food images using multimodal AI models to identify food items and estimate their nutritional content, including calories, proteins, carbohydrates, fats, sugar, and fiber. The Ingredient Safety Analysis module retrieves product information through barcode scanning or OCR-based label extraction and evaluates ingredients using a risk database to identify potentially harmful additives and preservatives. This enables users to make informed decisions regarding packaged food products.

The Personalized Diet Planning module generates cus-tomized dietary recommendations based on user health in-formation such as age, weight, height, activity level, and nutritional goals. All processed information is stored in a centralized MongoDB database, allowing efficient data man-agement and long-term progress tracking. The final results are displayed through an interactive dashboard that provides nutri-tional summaries, ingredient safety reports, and personalized health guidance, creating a complete ecosystem for intelligent nutrition management.

The system also ensures scalability by supporting modular expansion for future AI-driven health features. It is designed to provide fast, accurate, and user-friendly nutrition analysis suitable for real-world deployment.

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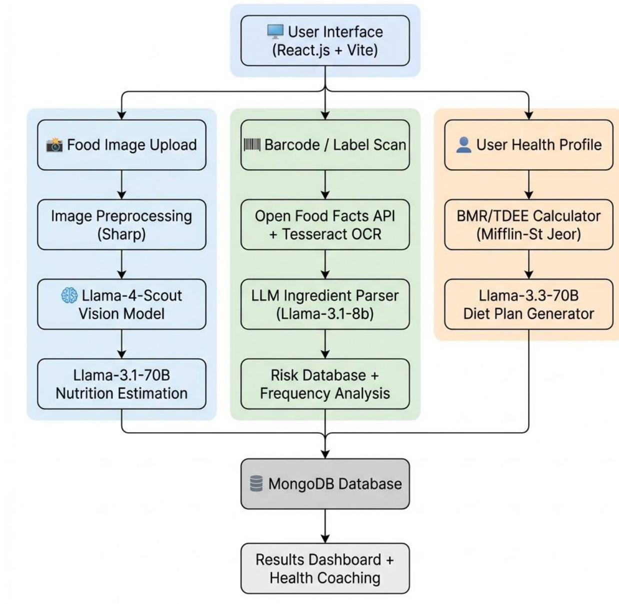

Fig. 6: System Architecture

V. RESULT AND ANALYSIS

The Nutralyze system was evaluated across three major functional modules: food recognition and nutrition estimation, ingredient safety analysis, and personalized diet recommenda-tion. Testing was conducted using a variety of food images, packaged food products, and user health profiles. The food recognition module successfully identified different food items from uploaded images and generated nutritional estimates in-cluding calories, proteins, carbohydrates, fats, sugar, and fiber. The multimodal AI models demonstrated reliable performance in analyzing food images captured under different conditions and were capable of handling diverse meal types.

The performance of the nutrition estimation module was evaluated by comparing the predicted calorie values with refer-ence nutritional values obtained from standard food composi-tion databases. The Mean Absolute Percentage Error (MAPE) was used as the evaluation metric. The results indicate that the proposed system achieved accurate calorie estimation for most food items, with an average MAPE of approximately 10.07%. Foods such as boiled eggs, bananas, and chapati showed minimal estimation error, while more complex dishes exhibited slightly higher deviations due to variations in ingredients and portion sizes.

The ingredient safety analysis module produced effective re-sults in extracting and interpreting ingredient information from packaged food products. Barcode scanning and OCR-based label extraction enabled accurate retrieval of ingredient lists, while the AI-powered ingredient parser successfully identified additives, preservatives, and other food compounds. The risk analysis mechanism accurately categorized ingredients accord-ing to their potential health impact and provided meaningful consumption recommendations, helping users make informed dietary decisions.

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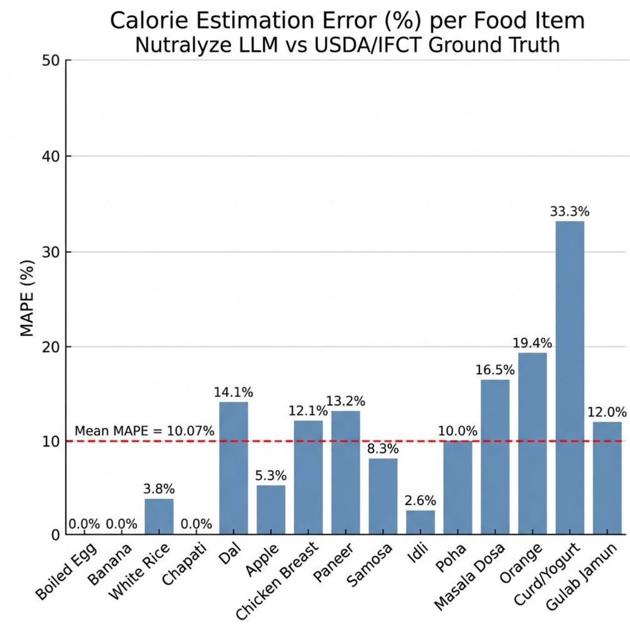

Fig. 7: Calorie Estimation Error (%) for Different Food Items.

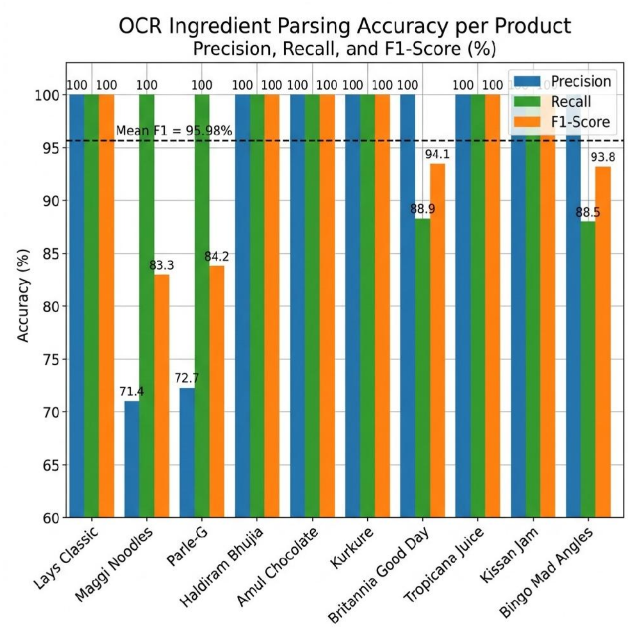

Fig. 8: OCR Ingredient Parsing Accuracy for Different Food Products.

The OCR-based ingredient extraction and parsing mod-ule was evaluated using multiple packaged food products. Precision, Recall, and F1-Score were calculated to measure the effectiveness of ingredient extraction and recognition.

The results demonstrate high extraction accuracy across most products, achieving an average F1-Score of approximately 95.98%. These findings confirm the reliability of the OCR and ingredient parsing pipeline in accurately identifying in-gredients from food labels and supporting subsequent safety analysis.

The personalized diet planning module generated cus-tomized meal recommendations based on user-specific factors such as age, gender, weight, height, activity level, and health goals. All processed information was stored and managed through the centralized database, allowing continuous dietary monitoring and progress tracking. The results demonstrate that Nutralyze provides a reliable and practical solution for nutrition analysis, food safety assessment, and personalized dietary guidance, making it suitable for real-world health and wellness applications.

VI. CONCLUSION

This paper presented Nutralyze, an intelligent nutrition analysis platform that combines food recognition, ingredient safety analysis, and personalized diet planning within a single system. By integrating multimodal AI models, OCR technol-ogy, and risk-based ingredient evaluation, the platform enables automatic nutritional assessment and food safety analysis from both food images and packaged food products. The experi-mental results demonstrated the effectiveness of the proposed approach, achieving a caloric estimation error (MAPE) of 10.07% and an OCR-based ingredient parsing accuracy (F1-score) of 95.98%. The system also provides personalized dietary recommendations based on user health profiles and nutritional requirements, helping users make informed food choices. Overall, Nutralyze offers a practical, scalable, and user-friendly solution for nutrition management, food safety assessment, and healthy lifestyle support.

VII. FUTURE WORK

Several enhancements can be incorporated into the Nutra-lyze system to further improve its performance and usabil-ity. Future work will focus on expanding the food image dataset and enhancing multimodal AI models to improve food recognition and nutritional estimation across diverse cuisines and complex dishes.The ingredient safety analysis module can be improved through multilingual OCR support, enhanced label reading capabilities, and integration with additional food safety databases. Future versions may also include real-time updates of food safety regulations and ingredient standards for more accurate risk assessment. The personalized diet planning module can be extended by integrating wearable devices and health monitoring systems to provide real-time dietary recommendations. Additionally, lightweight AI models and edge-computing techniques can be explored to improve efficiency and support deployment on mobile devices.

REFERENCES

[1] W. C. Knowler et al., “Reduction in the incidence of type 2 diabetes with lifestyle intervention or metformin,” New England Journal of Medicine, vol. 346, no. 6, pp. 393–403, 2002.
[2] A. Fakhrou, J. Kunhoth, and S. Al Maadeed, “Smartphone-based food recognition system using multiple deep CNN models,” Multimedia Tools and Applications, vol. 80, no. 21, pp. 33011–33032, 2021.
[3] C. Szegedy, V. Vanhoucke, S. Ioffe et al., “Rethinking the inception architecture for computer vision,” in Proc. IEEE CVPR, 2016, pp. 2818–2826.
[4] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, pp. 436–444, 2015.
[5] C. S. Won, “Multi-scale CNN for fine-grained image recognition,” IEEE Access, vol. 8, pp. 116663–116674, 2020.
[6] F. P. W. Lo, Y. Sun, J. Qiu et al., “Image-based food classification and volume estimation for dietary assessment: A review,” IEEE J. Biomedical and Health Informatics, vol. 24, no. 7, pp. 1926–1939, 2020.
[7] Z. Liu, Y. Lin, Y. Cao et al., “Swin Transformer: Hierarchical vision transformer using shifted windows,” in Proc. IEEE/CVF ICCV, 2021, pp. 9992–10002.
[8] G. Vinod, Z. Shao, and F. Zhu, “Image-based food energy estimation with depth domain adaptation,” in Proc. IEEE MIPR, 2022, pp. 262–267.
[9] W. Shao, W. Min, S. Hou et al., “Vision-based food nutrition estimation via RGB-D fusion network,” Food Chemistry, vol. 424, Art. no. 136309, 2023.

[10] A. Dosovitskiy, L. Beyer, A. Kolesnikov et al., "An image is worth 16×16 words: Transformers for image recognition at scale," arXiv preprint, 2021.
[11] Y. Chen, J. He, C. Czarnecki et al., "MetaFood3D: Large 3D food object dataset with nutrition values," arXiv preprint, 2024.
[12] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proc. IEEE CVPR, 2016.
[13] L. Jiang, B. Qiu, X. Liu, C. Huang, and K. Lin, "DeepFood: Food image analysis and dietary assessment via deep model," IEEE Access, vol. 8, pp. 47477–47489, 2020.
[14] G. Ciocca, G. Micali, and P. Napoletano, "State recognition of food images using deep features," IEEE Access, vol. 8, pp. 32003–32017, 2020.
[15] X. Zhao, L. Wang, Y. Zhang et al., "A review of convolutional neural networks in computer vision," Artificial Intelligence Review, vol. 57, Art. no. 99, 2024.
[16] S. Woo, J. Park, J.-Y. Lee, and I. S. Kweon, "CBAM: Convolutional block attention module," in Proc. ECCV, 2018, pp. 3–19.
[17] F. S. Konstantakopoulos, E. I. Georga, and D. I. Fotiadis, "A review of image-based food recognition and volume estimation AI systems," IEEE Reviews in Biomedical Engineering, vol. 17, pp. 136–152, 2024.
[18] L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
[19] D. W. Hosmer, S. Lemeshow, and R. X. Sturdivant, Applied Logistic Regression, Wiley, 2013.
[20] Meta AI, "Llama 3.1 Model Card," 2024. [Online]. Available: https://github.com/meta-llama/llama-models