2025 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS) | 979-8-3315-4294-8/25/$31.00 ©2025 IEEE | DOI: 10.1109/I2CACIS65476.2025.11101084

NutriGuru, a Food Detection and Nutrition Tracking Mobile Application based on Deep Learning and Computer Vision Techniques

Leong Jia Min[1], Ghassan Saleh Al-Dharhani * [2,3], Kasthuri Subaramaniam [4], Muhammed Basheer Jasser[5], Samuel-Soma M. Ajibade [5], Hui Na Chua [5]

[2]*Aden Community College, Aden, Yemen*

[1,3]*Institute of Computer Science and Digital Innovation, UCSI University, 56000 Kuala Lumpur, Malaysia*

[4]*Department of Decision Science, Faculty of Business and Economics, University of Malaya, 50603 Kuala Lumpur, Malaysia*

[5]*School of Computing and Artificial Intelligence, Faculty of Engineering and Technology, Sunway University, No. 5, Jalan Universiti, Bandar Sunway, 47500 Selangor Darul Ehsan, Malaysia*

1002161828@ucsiuniversity.edu.my, ghassanxyz@gmail.com (*), ghassan@ucsiuniversity.edu.my, skasthuri@um.edu.my, basheerj@sunway.edu.my, samuelma@sunway.edu.my, huinac@sunway.edu.my

***Abstract*— In this rapidly moving digital world, dietary decisions are highly influenced by technology; however, the prevalence of unhealthy eating is unconscionably rising, especially in Malaysia, where many individuals are suffering from non-communicable diseases (NCDs) such as obesity, diabetes, and hypertension. Hence, NutriGuru aims to develop a mobile application based on computer vision technology, YOLOv8 (You Only Look Once) model, to detect Malaysian dishes. The application operates by using a camera or search feature to detect Malaysian dishes with estimated portion sizes. It retrieves the nutritional information, logs it to the daily tracker, and provides personalized dietary recommendations. The paper contributes to research on innovative food detection and nutrition tracking tools and offers a convenient way for users to easily track Malaysian dishes and address various health issues related to diet.**

Keywords*— *Food Detection, Nutrition Tracking, Malaysian Dishes, YOLOv8

I. Introduction

Non-communicable diseases (NCDs) are one of the fastest-growing health concerns in Malaysia. According to the World Health Organization, 74% of Malaysian deaths resulted from NCDs [1]. The latest National Health and Morbidity Survey 2023 just revealed shocking results where 2.5% of adults in Malaysia are currently diagnosed with four non-communicable diseases (NCDs), including diabetes, hypertension, high cholesterol, and obesity. Malaysians with four NCDs have the highest probability of getting heart disease and stroke [2]. While proper diet remains one of the most effective ways of nutrition management, most nutrition management techniques against the onset of NCDs have traditionally been very time-consuming and require much effort. Thus, mobile technology is introduced as a promising approach that offers accessible tools to support dietary tracking or nutrition education. However, existing nutrition applications have several critical challenges that need to be addressed, especially in Asian countries. These involve errors in food identification, scarcity of local dishes' datasets, and poor user experience [3].

In response to these issues, NutriGuru will be introduced as an innovative nutrition-tracking mobile application specifically designed for Malaysian dishes. By integrating advanced techniques of computer vision and training on customized Malaysian food datasets, the application can accurately detect Malaysian food items with their estimated portion size and retrieve nutritional values. Beyond simple tracking, it monitors risk by highlighting nutritional deficiencies, and health risks arising from dietary patterns.

This paper aims to fill the gap by developing a more culturally appropriate tool for daily food intake tracking and an educational platform for the adoption of healthier eating behaviour for Malaysians. This approach contributes to the broader effort of addressing the rising prevalence of NCDs in Malaysia.

II. Literature Review

A. Introducing Food Detection Technology

1) Computer Vision and Image Processing: Food detection, classification and analysis have been the subjects of extensive research for various applications in connection with the pattern of eating and dietary assessment. In most proposed systems, food images are captured by people using their smartphones [4]. A computer vision system is then used to collect and extract detailed information about food, including size, appearance, shape, and surface colour that humans cannot observe. In this way, this approach helps to prevent human errors and ensures better accuracy [5]. During food detection, computer vision relies heavily on image information processing and analysis. Recent image processing techniques are now categorized into three different levels: (1) low-level processing, (2) mid-level processing, and (3) high-level processing [6].

2) Machine Learning Algorithms Used in Food Detection: Although food detection systems are very useful to everyone, food classification can sometimes misidentify some existing food items and most users often find manually typing each meal inconvenient. Thus, food detection can be useful in reducing time consumption [7]. This section discusses the different approaches of deep learning models designed by the researchers, including algorithms, implemented systems, accuracy and the datasets used, shown in Table I.

TABLE I. COMPARISON OF FOOD DETECTION TECHNIQUES USING DEEP LEARNING

Ref.	Dataset	Algorithm	System	Accuracy
Kawano and Yanai [8]	UEC-FOOD100	DCNN	Mobile Devices	72.26%
Kagaya et al. [9]	Food-domain images	CNN	-	93.8%
Srigurulekha and Ramachandran [10]	Food 101	CNN	Computer Software	86.85%
Phiphiphatphaisit and Surinta [11]	ETH Food-101	MobileNet	Mobile Devices	72.59%
Wang et al. [12]	FewFood-50	YOLO-SIMM	Computer Software	90.06%
Romadhon et al. [13]	Image data training using Google Colab	YOLO	Computer Software	91%
Sun et al. [14]	UECFood-100, UECFood-256	MobileNet-YOLO	Mobile Application	80%

3) Food Datasets and Pre-trained Models: Food databases have been constructed to serve different objectives in multiple research projects. Several researchers gathered food specifically to develop efficient food image classification. Sengur et al. [15] evaluated food classification accuracy using deep features from AlexNet and VGG16 on three datasets: FOOD-5K, FOOD-11, and FOOD-101, achieving accuracies of 99%, 88.08%, and 79.86%, respectively. Another fact observed in the current research with food images is the development of local food datasets originating from images collected through several studies. Subhi and Ali [16] introduced a new food image dataset combining FOOD-101 with 3,300 local Malaysian dishes. Additionally, the creation of food image datasets has helped researchers in training implement applications for the identification of food recipes and portion sizes. X. Wang et al. [17] introduced a real-world application that allows users to search for recipes using their dataset; and compared this approach to a similar dataset, ETHZ Food-101.

4) Process of Integrating Trained Models into Mobile Applications: After finalizing the dataset and developing a machine learning model, the next step is to integrate the deep learning model into a mobile application. The general conceptual framework of smartphone application for food detection consists of two components: a mobile application for real-time food recognition and a training environment for Deep CNN Food Recognition Models. To provide real-time analysis, the mobile application is intended to capture images by utilizing the integrated camera of the device and apply the model's inference to identify food items in the picture [18].

5) Review of Existing Food and Nutrition API: In the development of a food detection app, the integration of comprehensive databases and APIs is crucial to improve user experience, ultimately providing users with rich content beyond just identifying food. According to Table II, all the food and nutrition APIs mentioned have an accuracy of 90% or above, which shows the potential use of these APIs. These APIs offer food and recipe databases with diverse levels of information and unique features.

TABLE II. COMPARISON OF NUTRTION API FEATURES

Feature	FatSecret API [19]	Edamam API [20]	Nutritionix API [21]
Food Database	17,000+ recipes	2.3 million recipes, 900,000 food items	1,166,080 food items
Data Coverage	Stronger focus on United States	Global Reach	Global Reach
Accuracy	>90%	95%+	>92%
API Feature	1. Access to recipe data 2. Highest-quality search capability 3. Custom food & exercise tracker 4. Recipe builder & nutritional analysis 5. Barcode scanning 6. Allergens and Dietary Preferences	1. Food Database API 2. Nutrition Analysis API 3. Recipe Search API 4. Recipe Content Management API 5. Food Analytics and Recipe Trend Analysis 5. Meal Recommendation API 6. AI Assistant	1. Natural Language Processing Feature 2. Barcode Scanning 3. Common Foods Database
Cost	Free and paid plans	Free and paid plans	Free and paid plans
Language Support	24 languages in 56+ countries	Supports multiple languages	Supports multiple languages
Application	iNutritionApp, MyFitnessPal	Yummly	Lifesum, Noom

B. Existing Mobile Apps for Nutrition Tracking

Within this broad range of applications, the area of mobile applications has turned out as effective solutions useful for monitoring and controlling various aspects of health related to nutrition. According to Table III, each of the mentioned applications has its standout feature. For example, Foodvisor [22] provides macro-tracking and tracking activity levels, which is suitable for those who aim for muscle-building; CalorieMama [23] has a step counter feature for tracking the users' steps within a day for a healthier lifestyle; and Nutricapture [24] offers AI-powered chat for users to interact and ask specific nutrition questions in real time.

TABLE III. COMPARISON TABLE OF EXISTING NUTRITION APPLICATIONS WITH NUTRIGURU

Features	NutriGuru	Foodvisor	CalorieMama	Nutricapture
Food Recognition	✔	✔	✔	✔
Calorie Tracking	✔	✔	✔	✔
Risk Assessment	✔	✖	✖	✖
Personalization	✔	✔	L	L

✔ = Yes ✖ = No L = Limited

These applications also provide basic food recognition and logging features to track their daily meal and view nutritional information. Thus, the main aim of this proposed project is to create a nutrition tracking application that prioritizes better food recognition features, a risk assessment feature used to analyze user's dietary patterns for Malaysians.

III. Analysis and Discussion

A. *Questionnaire*

An online questionnaire in Google Forms was created to collect feasible data regarding food consumption, attitudes towards nutrition, and interest in using an application that can identify foods and indicate daily intake of nutrients. For the sample size, participant selection will be restricted to Malaysians and other foreigners living in the country, to collect 100 participants for the survey that diverse viewpoints on consumption patterns, familiarity with Malaysian food, and attitudes towards diet are captured within the study.

1) Section A: Demographic Information where the respondent demographics in terms of age, gender, job, education level, nationality, geographical location and level of awareness regarding Malaysian food will be obtained.

2) Section B: Focus on respondents' present dietary behaviours, and their perceptions of nutrition information regarding Malaysian foods, and their awareness of Malaysian dietary recommendations.

3) Section C: Seeks to establish difficulties which the respondents face in following a healthy diet and comprehending nutritional labels. The attention will be paid to the definition of the major threats that NutriGuru can mitigate in the development of the application.

4) Section D: This section aims to identify which of the features in the list the respondents believe are most useful and relevant for helping them achieve their dietary objectives, which allows NutriGuru to include these in its development.

B. *Analysis Summary*

There is a serious gap between nutrition knowledge and actual practice. While many respondents acknowledged that nutrition and balanced dieting were important, few managed to translate this when going out to eat or making healthy choices. This was even further complicated by the confusion raised in searching for reliable nutritional information about Malaysian cuisine, estimating portion sizes, and navigating high-calorie content across traditional dishes. The cultural expectations and also increased access to high-calorie foods, as indicated in the survey. The proposed NutriGuru application demonstrated the following interests: tracking daily nutrient intake and identifying Malaysian dishes. The respondents prefer an easy-to-use application to give them accurate nutritional information, a variety of food databases, and the ability to provide personalized recommendations. The ability to identify and estimate portions of Malaysian dishes was highly coveted, followed closely by customization of the app based on individual health goals and dietary preferences. Synthesis

C. *Model Training Process*

The section represents the process of training a customized YOLOv8 model using Roboflow and Google Colab to conduct food detection.

1) Dataset Preparation: The first part of the methodology starts with data collection, where users upload 80 images per class on Roboflow. The classes are created differently for each food type before annotation. Although the size of the dataset is limited, it provides a solid foundation for initial model development and can be extended for future work.

2) Annotation and Preprocessing: After establishing the classes in Roboflow, each food items in the uploaded images were thoroughly annotated. The bounding boxes were drawn around each food item with precision in the user-friendly interface that Roboflow provided, to improve the accuracy at the level of the training dataset. The dataset was resized to 320x320 pixels and data augmentation was also applied to increase both variability and robustness of the model.

3) Model Training: The preprocessed dataset was exported from Roboflow and imported into Google Colab, which then used the heavy computational power of GPU resources for training. Therefore, the YOLOv8 model was allowed to converge over multiple epochs and thus allowed the identification of an optimum between accuracy and inference time. To further improve the accuracy of YOLOv8 model, the training was carried out for several epochs and the mAP and loss functions were used to fine-tune the model.

4) Exporting the Model: After training the custom YOLOv8 model, it was converted and saved in TFLite format. This conversion is necessary to enable compatibility with mobile devices and allow for on-device, efficient inference. Lastly, a text file containing all class labels was created for easy reference during model deployment.

As shown in Fig. 1, the results in YOLOv8 model achieved about 87.1% detection accuracy on the validation set, hence robust performance under real-world varied conditions on detecting objects.

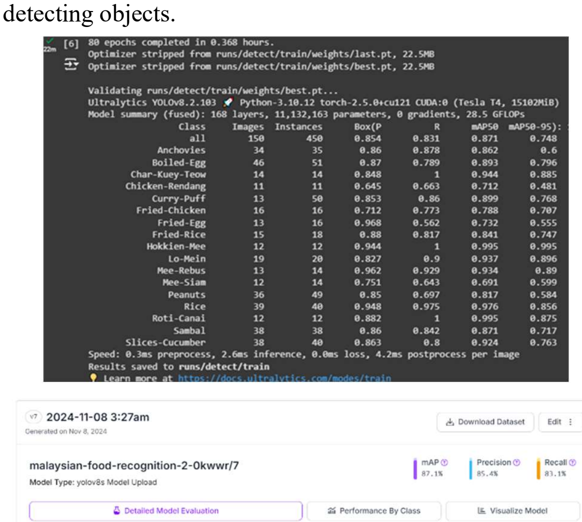

Fig. 1. shows a breakdown of a trained YOLOv8 model with class-wise mAP values that evaluate detection for each object category, in addition to overall metrics – 87.1% mAP, which implies strong average detection accuracy, 85.4% precision, and 83.1% recall rate.

According to Fig. 2, the model shows impressive results on object detection tasks. The training losses have been steadily improving, with box, classification, and DFL losses decreasing by about 65%, 89%, and 31%, respectively. Both precision and recall are over 80% as they showed high accuracy, keeping a robust mAP of 85% at 50% IoU and 75% across 50-95% IoU thresholds. Therefore, throughout training, the validation metrics were largely flat, which indicated good generalization without overfitting and suitable for practical purposes.

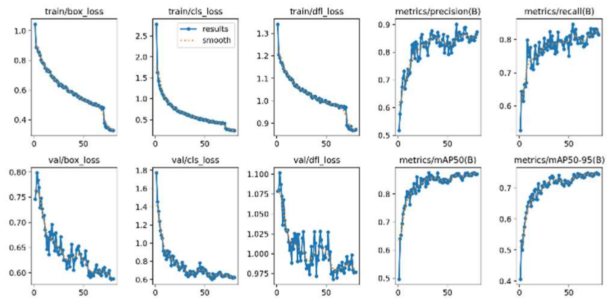

Fig. 2. Confusion Matrix of Trained YOLOv8 Model.

D. System Workflow Diagram

The following flowchart in Fig. 3 represents how NutriGuru operates. The first point in the user journey is the "Start" point and users can either use a device camera to capture their food or input the food on their own. For the camera option, the app identifies the food along with its estimated portion size. Both methods then show nutritional value, recommend nutrients, and estimate the total nutrient intake for the day. Users are allowed to log multiple meals and start a new entry, which forms a continuous loop for comprehensive nutrition management.

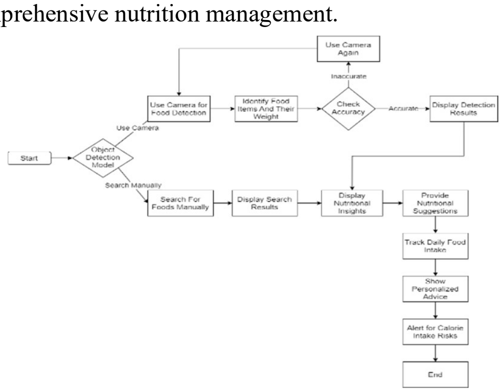

Fig. 3. presents the workflow of the NutriGuru system where users input foods using a camera or manually to get nutritional analysis.

E. User Interface Design of NutriGuru

Fig. 4 shows the main pages of NutriGuru, which consist of Tracking, Logging, and Profile Page. On the left panel, it has a daily insight section that shows the user's calorie budget and their nutrient intake, which are divided into macronutrients such as proteins, carbohydrates, and fats. In the middle, users can log their meals by either taking pictures of the food items or searching directly for them. The right panel summarizes information on the user's profile: age, gender, weight, height, and BMI, as well as personal feedback on caloric intake and recommendations on how to keep their diet balanced.

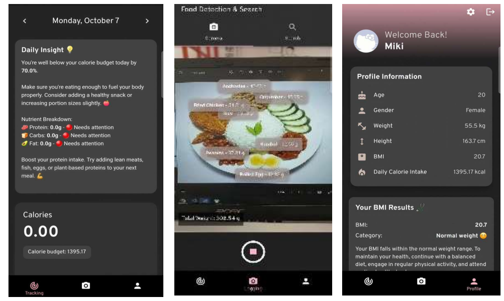

Fig. 4. The main page of NutriGuru includes Tracking (left), Logging (middle), and Profile (right) sections.

F. User Flow of NutriGuru

1) Profile Setup: After a user account is created, users begin their journey by developing a profile with basic information such as age, weight, height, diet preference, and weight goals. Once verified, NutriGuru determines the individual user's Body Mass Index (BMI), and the proposed daily caloric intake varies depending on the user (Fig. 5).

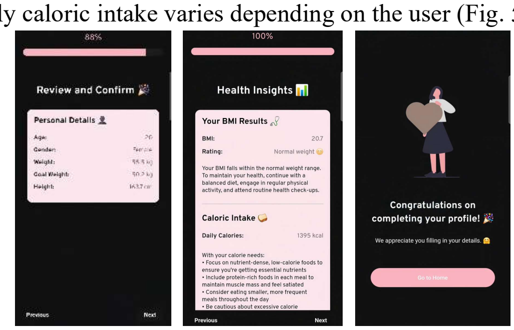

Fig. 5. describes the complete procedure of setting up the profile, with steps presented on how users can input age, weight, height, and goal weight.

2) Logging – Food Detection using Camera and Search Function: This feature allows users to record their meals by scanning food items using the device's camera. The portion size of the detected food is predicted using bounding boxes and later converted into real-life measurements. After scanning, users may click the "View Results" button to access detailed information about the identified food items (Fig. 6a). Users also have the option of inputting their food intake manually via a search function (Fig. 6b). This is helpful for cases where the camera is unable to identify the food item.

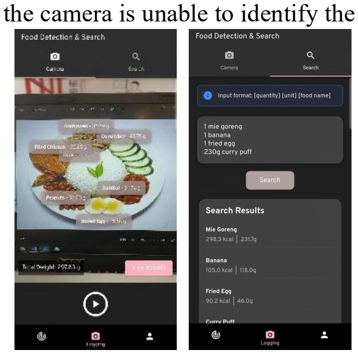

Fig. 6. Food logging methods: (a) Camera detection with portion estimation; (b) Manual food entry with customized serving sizes

3) View Results: In Fig. 7, when a user clicks on the "View Results" button, the user is directed to the next page where all the food items that the user has input from the camera or search are listed together with breakdowns of calories, macronutrients, and micronutrients. Besides, it also offers an obesity score, recommended weight and a meal recommendation that will guide them on their overall health check for every meal. If users wish to add the food item to the tracker, they can click on the "Add This Food" button.

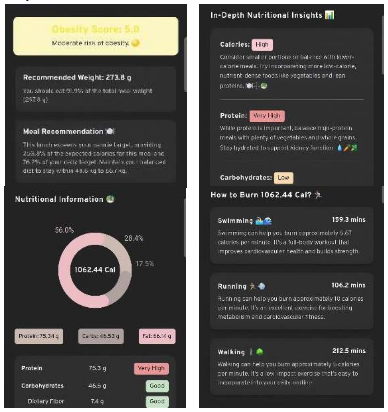

Fig. 7. presents the result page containing identified food items, nutrient breakdown, obesity score, meal advice, with a feature to add to the tracker.

4) View Tracker: The tracker is intended to assist users in viewing their daily total calorie usage and macronutrient ratios. This makes it possible for them to record different meals they take every day as breakfast, lunch, dinner, and snacks taken in between (see Fig. 8).

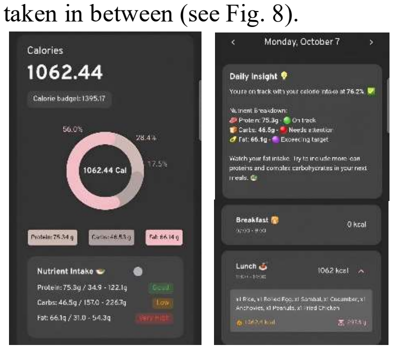

Fig. 8. shows a tracker page that summarizes the user's total daily calories, macronutrient ratio, and classifications of meal entries for diet tracking.

5) Profile Settings: In Fig. 9, Users can modify their details by altering their username and height. When these changes are made, the changes in height will impact BMI as well as daily caloric intake. With wellness efforts, while keeping personal information up-to-date.

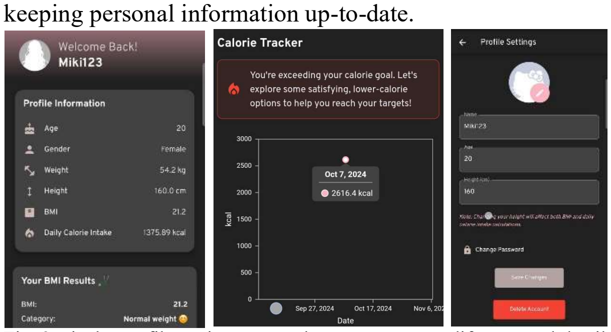

Fig. 9. is the profile settings page where users can modify personal details such as name and height and change a new profile photo.

6) Weight Tracking: This feature is incorporated to track progress towards a set weight loss target. Users can input new weights and get motivational messages based on the goal achievement of the user. As the user progresses through a weight loss plan, a graph visually illustrates their weight to help them track their progress easily, as shown in Fig. 10.

Fig. 10. displays a weight tracking graph that visually tracks the user's weight progress over time.

IV. Evaluation

A. System Testing

The system testing for the NutriGuru application will be conducted to ensure that all functionalities are in tune with each other for flawless management of the users' nutritional, weight, and healthy lifestyle goals. The testing will verify the accuracy of data tracking in food logging, calorie intake, weight progress, and custom recommendations.

As a result, all 54 test cases were executed successfully, proving that NutriGuru has met its functional requirements and runs smoothly through all its features. This range of system testing ensures that the tracking accuracies across food logging, calorie intake, and weight progress, along with customized recommendations, problems, bugs, or inconsistencies that would hamper user experiences or system reliability.

B. User Acceptance Testing (UAT) and TAM Integration

To evaluate the user acceptance test on the NutriGuru application, the study was conducted on fifteen (15) respondents. Respondents were asked to complete a set of questionnaires divided into six parts, with varied questions. Participants were also requested to rate the application features based on a 5-point Likert scale that consisted of strongly disagree, disagree, neutral, agree and strongly agree.

The outcome of the User Acceptance Test of the NutriGuru application came out to be very positive, with an overall mean score of 4.75. The rating scores included 4.77 for the user login and registration, 4.55 for the accuracy of food detection, 4.69 for the clarity of nutrition information, and 4.89 for the Profile Page. Following the Technology Acceptance Model (TAM) framework, the evaluation scores indicate high acceptance from the user: the high Perceived Usefulness (PU) of 4.78 (food tracking accuracy) and outstanding Perceived Ease of Use (PEOU) score of 4.83 (interface usability) collectively point to positive behavioral intention towards further adoption.

This will aim at the identified pain points in the effort toward overall user satisfaction, and more intuitive and efficient interaction with the system.

- Improve error messages, food detection accuracy, and graphical representation of calorie tracking.
- Allow users to skip the login after registration, support biometric login, and apply OTP email verification.

C. Acceptance Testing

This acceptance test will ensure that all the objectives and requirements defined in this project are met. The results for the corresponding objective and requirements are given in Table IV.

TABLE IV. ACCEPTANCE TESTING

Objectives	Results of Testing
To study the strengths and weaknesses of existing nutrition-tracking applications currently available in the market	The goal was achieved through a comprehensive review of existing nutrition apps, with documented analysis regarding features, strengths, and limitations of major competitors in the market.
To design the nutrition-tracking app by converting user's requirements into a system design such as user interfaces, database design, and the integration of APIs	The goal was achieved by successfully creating a complete system architecture such as a use case diagram, entity relationship diagram, and sequence diagram that aligns with user requirements.
To evaluate the effectiveness of nutrition app by conducting surveys to gather relevant information and user feedback	The goal was achieved by carrying out a user acceptance test where feedback was gathered through surveys, and the responses proved to be highly positive and showed a strong recommendation for app.

V. CONCLUSION

NutriGuru has been developed effectively using the Flutter framework to address the key nutritional gaps in today's fast-moving lifestyle. Contrastingly to previous efforts, which focused on general food types, NutriGuru sets itself apart by fine-tuning the YOLOv8 model for Malaysian cuisine with a high mAP accuracy of 87.1%. High satisfaction with the app has been demonstrated through continuous user feedback. NutriGuru is particularly useful at present, where people are so busy in their lives that most of them prioritize convenience rather than health.

The application is extremely useful for individuals who can barely manage enough time to care about nutrition. NutriGuru makes food intake tracking and comprehension less complex for an individual; thus, it is much easier to maintain proper nutrition even when life gets in the way. Future enhancements will include food detection algorithms and customization of the user experience based on health-related questions.

REFERENCES

[1] "Noncommunicable Diseases," PAHO/WHO | Pan American Health Organization. Accessed: May 22, 2024. [Online]. Available: https://www.paho.org/en/topics/noncommunicable-diseases

[2] Ministry of Health Malaysia, "NHMS 2023," National Institutes of Health, Ministry of Health Malaysia. Accessed: May 22, 2024. [Online]. Available: https://iku.gov.my/nhms-2023

[3] C. Fakih El Khoury, M. Karavetian, R. J. G. Halfens, R. Crutzen, L. Khoja, and J. M. G. A. Schols, "The Effects of Dietary Mobile Apps on Nutritional Outcomes in Adults with Chronic Diseases: A Systematic Review and Meta-Analysis," *J Acad Nutr Diet*, vol. 119, no. 4, pp. 626–651, Apr. 2019, doi: 10.1016/j.jand.2018.11.010.

[4] P. Pouladzadeh, A. Yassine, and S. Shirmohammadi, "FooDD: Food detection dataset for calorie measurement using food images," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Springer Verlag, 2015, pp. 441–448. doi: 10.1007/978-3-319-23222-5_54.

[5] L. Zhu, P. Spachos, E. Pensini, and K. N. Plataniotis, "Deep learning and machine vision for food processing: A survey," *Curr Res Food Sci*, vol. 4, pp. 233–249, 2021, doi: 10.1016/j.crfs.2021.03.009.

[6] K. Patel, "Image Processing Tools and Techniques Used in Computer Vision for Quality Assessment of Food Products: A Review," 2015. [Online]. Available: www.jakraya.com/journal/ijfqs

[7] W. Shimoda and K. Yanai, "Foodness proposal for multiple food detection by training of single food images," in *MADiMa 2016 - Proceedings of the 2nd International Workshop on Multimedia Assisted Dietary Management, co-located with ACM Multimedia 2016*, Association for Computing Machinery, Inc, Oct. 2016, pp. 13–21. doi: 10.1145/2986035.2986043.

[8] Y. Kawano and K. Yanai, "Food image recognition with deep convolutional features," in *UbiComp 2014 - Adjunct Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, Association for Computing Machinery, Inc, 2014, pp. 589–593. doi: 10.1145/2638728.2641339.

[9] H. Kagaya, K. Aizawa, and M. Ogawa, "Food detection and recognition using convolutional neural network," in *MM 2014 - Proceedings of the 2014 ACM Conference on Multimedia*, Association for Computing Machinery, Nov. 2014, pp. 1085–1088. doi: 10.1145/2647868.2654970.

[10] K. Srigurulekha and V. Ramachandran, "Food image recognition using CNN," in *2020 International Conference on Computer Communication and Informatics (ICCCI)*, IEEE, Jan. 2020, pp. 1–7. doi: 10.1109/ICCCI48352.2020.9104078.

[11] S. Phiphiphatphaisit and O. Surinta, "Food Image Classification with Improved MobileNet Architecture and Data Augmentation," in *Proceedings of the 2020 The 3rd International Conference on Information Science and System*, New York, NY, USA: ACM, Mar. 2020, pp. 51–56. doi: 10.1145/3388176.3388179.

[12] Y. Wang, J. Wu, H. Deng, and X. Zeng, "Food Image Recognition and Food Safety Detection Method Based on Deep Learning," *Comput Intell Neurosci*, vol. 2021, pp. 1–13, Dec. 2021, doi: 10.1155/2021/1268453.

[13] F. Romadhon *et al.*, "Food Image Detection System and Calorie Content Estimation Using Yolo to Control Calorie Intake in the Body," in *E3S Web of Conferences*, EDP Sciences, Dec. 2023. doi: 10.1051/e3sconf/202346502057.

[14] J. Sun, K. Radecka, and Z. Zilic, "FoodTracker: A Real-time Food Detection Mobile Application by Deep Convolutional Neural Networks," Sep. 2019.

[15] A. Sengur, Y. Akbulut, and U. Budak, "Food Image Classification with Deep Features," in *2019 International Artificial Intelligence and Data Processing Symposium (IDAP)*, IEEE, Sep. 2019, pp. 1–6. doi: 10.1109/IDAP.2019.8875946.

[16] M. A. Subhi and S. Md. Ali, "A Deep Convolutional Neural Network for Food Detection and Recognition," in *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, IEEE, Dec. 2018, pp. 284–287. doi: 10.1109/IECBES.2018.8626720.

[17] Xin Wang, D. Kumar, N. Thome, M. Cord, and F. Precioso, "Recipe recognition with large multimodal food dataset," in *2015 IEEE International Conference on Multimedia & Expo Workshops (ICMEW)*, IEEE, Jun. 2015, pp. 1–6. doi: 10.1109/ICMEW.2015.7169757.

[18] A. Fakhrou, J. Kunhoth, and S. Al Maadeed, "Smartphone-based food recognition system using multiple deep CNN models," *Multimed Tools Appl*, vol. 80, no. 21–23, pp. 33011–33032, Sep. 2021, doi: 10.1007/s11042-021-11329-6.

[19] "FatSecret," FatSecret. Accessed: Jun. 03, 2024. [Online]. Available: https://platform.fatsecret.com/platform-api

[20] "Edamam," Edamam. Accessed: Jun. 04, 2024. [Online]. Available: https://www.edamam.com/

[21] "Nutrition API by Nutritionix," Nutritionix. Accessed: Jun. 04, 2024. [Online]. Available: https://www.nutritionix.com/business/api

[22] "Foodvisor," Foodvisor. Accessed: Jun. 05, 2024. [Online]. Available: https://www.foodvisor.io/en/

[23] "Calorie Mama," Calorie Mama. Accessed: Jun. 05, 2024. [Online]. Available: https://www.caloriemama.ai/#CalorieMama

[24] "Nutricapture," Nutricapture. Accessed: Jun. 06, 2024. [Online]. Available: https://nutricapture.com/