

Implementation of the YOLOv8 Model for Component Detection and Image-Based Free Nutritional Food Nutrition

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Abstract : The Free Nutritious Food Program (Makan Bergizi Gratis/MBG) is a government initiative aimed at improving the nutritional status of school-age children through the provision of balanced meals. However, the identification of food components and the provision of nutritional information are still commonly performed manually, which can be time-consuming and less efficient. This study aims to implement the YOLOv8 model to detect food components in image-based MBG meal packages and integrate the detection results with an artificial intelligence-based nutritional information service. The dataset was collected from MBG meal packages at the Sumolawang Nutrition Fulfillment Service Unit (SPPG), Mojokerto, and consisted of food images representing 19 classes. The images were annotated using bounding boxes and processed through training, validation, and testing stages. YOLOv8n was implemented as the object detection model, while Roboflow was used for dataset management and model deployment. The detected food components were subsequently processed through an AI-based API to obtain estimated nutritional information, including energy, protein, carbohydrates, fat, and fiber. The system was implemented as a web application using Python and Flask and evaluated through functional black-box testing. The testing results showed that the system successfully detected five food objects in a test image, with an average confidence score of 84% and an inference time of approximately 4.84 seconds. The system was also able to present nutritional information and handle detection or API failures. However, quantitative model evaluation using precision, recall, and mean Average Precision (mAP), as well as validation of nutritional estimates against measured portion sizes or established nutritional standards, remains necessary. The study demonstrates the feasibility of integrating YOLOv8-based food detection with an AI-based nutritional information service to support image-based monitoring of MBG meal components.

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Introduction

Providing balanced nutrition to school-age children is a crucial factor in improving the quality of human resources because it impacts physical growth, cognitive development, and learning abilities.

Various studies have shown that insufficient energy and protein intake can reduce learning concentration, hinder cognitive development, and increase the risk of stunting and anemia. Therefore, providing nutritious food through educational institutions is an effective strategy for improving children's nutritional status equitably and sustainably (UNICEF, 2023).

To implement this strategy, the Indonesian government launched the Free Nutritious Food Program (MBG), which aims to provide nutritionally balanced food packages that include sources of carbohydrates, animal protein, vegetable protein, vegetables, and fruits. This program is expected to improve the nutritional quality of students while supporting the achievement of development goals in health and education. However, program implementation still faces challenges in the quality control process and the appropriateness of menu composition. Manual verification of food packages is relatively time-consuming, prone to subjectivity, and ineffective when applied to large-scale food distribution (Ministry of Health of the Republic of Indonesia, 2023).

Advances in artificial intelligence technology, particularly computer vision, offer opportunities to improve the efficiency of food verification processes through automated image analysis. One emerging approach is Image-Based Dietary Assessment (IBDA), a digital image-based food assessment method that utilizes deep learning algorithms to identify food types and estimate their nutritional content. This approach has been reported to produce estimates of energy and macronutrient intake with a high degree of accuracy compared to conventional methods such as food recall and manual weighing (Chen et al., 2022) (Fang et al., 2021).

In the development of computer vision-based systems, the You Only Look Once (YOLO) algorithm is a widely used object detection method due to its ability to rapidly detect multiple objects in a single processing stage. The latest version, YOLOv8, offers improvements in network architecture, computational efficiency, and detection accuracy, particularly for small objects and overlapping objects. These advantages make YOLOv8 a potential model for detecting various food components in a single serving (Jocher & Chaurasia, 2023) (Purnomo, 2025).

However, previous research has generally focused on food type detection for individual consumption recording, dietary management, or calorie estimation. Integration of multi-object detection with macronutrient content estimation in the context of Free Nutritious Meal Program evaluation is still relatively limited. Furthermore, some studies only calculate energy values without considering protein, fat, and carbohydrate content, which are important indicators in evaluating the nutritional quality of school menus. This situation indicates a research opportunity in developing a system capable of detecting food components and providing nutritional information automatically to support the monitoring process of the Free Nutritious Meal Program (MBG). (Chen et al., 2025) (Mansouri & Qureshi, 2023).

Based on these problems, this study proposes the implementation of the YOLOv8 model to detect food components in Free Nutritious Food packages based on images and integrate it with a nutritional database to generate automatic estimates of energy, protein, fat, and carbohydrates. The developed system is implemented in the form of a web-based application so that it is able to provide information on the results of detection and nutritional estimates quickly, objectively, and measurably. The contribution of this study lies in the development of an integrated system that combines YOLOv8-based multi-object detection with macronutrient estimation in the context of the Free Nutritious Food Program. The results of this study are expected to support the process of monitoring nutritional quality more efficiently while expanding the application of computer vision in the fields of public health and food technology.

This study aims to develop an image-based food component detection system for Free Nutritious Food (MBG) packages using the YOLOv8 model integrated with a nutritional database to automatically estimate energy, protein, fat, and carbohydrate content. Furthermore, this study aims to evaluate the performance of the detection model using precision, recall, and mean Average Precision (mAP) metrics, as well as assess the accuracy of nutritional value estimates by comparing the system results with manual calculations or applicable nutritional standards.

Literature review

Free Nutritious Food Program (MBG)

The Free Nutritious Food Program (MBG) is a government program aimed at improving the nutritional status of school-age children by providing balanced meals containing carbohydrates, animal protein, vegetable protein, vegetables, and fruit. Meeting these nutritional needs plays a crucial role in supporting physical growth, cognitive development, and students' learning abilities (Ministry of Health of the Republic of Indonesia, 2023) (World Health Organization, 2022).

However, the implementation of the MBG program still faces challenges in the quality control process and menu composition compliance. Manual food package verification tends to be time-consuming, prone to subjectivity, and inefficient for large-scale distribution. Therefore, a computer vision-based approach capable of automatic, objective, and measurable detection and verification of food components is needed to support the quality evaluation of MBG packages (UNICEF, 2023) (Bappenas, 2024).

Image-Based Dietary Assessment (IBDA)

Image-Based Dietary Assessment (IBDA) is a dietary intake assessment approach that utilizes digital images as the primary data source. In this method, food is recorded through photographs, then analyzed to identify food types and estimate their nutritional content using computer vision and deep learning algorithms. IBDA was developed as an alternative to conventional methods such as food recall and food weighing, which are considered inefficient and dependent on respondents' memory and compliance (Chen et al., 2022) (Fang et al., 2021).

Recent studies have shown that IBDA can provide fairly accurate estimates of energy and macronutrient intake, especially when combined with modern deep learning models. However, the main challenges of IBDA lie in the variation in food presentation, differences in lighting, shooting angles, and overlap between food items. Therefore, the success of the IBDA approach depends heavily on the ability of the object detection algorithm used to accurately recognize each food component (Mansouri & Qureshi, 2023) (Purwati et al., 2025).

Computer Vision

Computer vision is a branch of artificial intelligence that enables computer systems to understand and analyze visual information from images or videos. In the context of this research, computer vision is used to recognize and localize food components contained in a single MBG package. This process includes object identification, determining object position within the image, and classifying food types based on their visual characteristics (Goodfellow et al., 2021) (Szeliski, 2022).

The use of computer vision in food analysis enables digital images to serve not only as visual documentation but also as a source of quantitative data that can be further processed. This approach enables the system to automatically and consistently verify food components, making it highly suitable for the monitoring needs of large-scale MBG programs.

Deep Learning and Convolutional Neural Networks (CNN)

Deep learning is a subfield of machine learning that uses layered artificial neural networks to learn hierarchical data representations. In image processing, the most widely used architecture is the Convolutional Neural Network (CNN), specifically designed to automatically extract visual features such as color, shape, texture, and pattern. CNNs have proven highly effective in various computer vision tasks, including food object classification and detection (Goodfellow et al., 2021) (LeCun, 2022).

In this study, CNN served as the underlying architecture of the YOLOv8 model. CNN's advantage lies in its ability to recognize complex visual patterns without the need for manual feature design. This is particularly important in the context of MBG food, which has a variety of appearances and presentations.

YOLO and YOLOv8

YOLO (You Only Look Once) YOLO (You Only Look Once) is a deep learning-based object detection algorithm that works with a single-stage detection approach. YOLO detects and classifies objects in a single processing stage, resulting in a high inference speed compared to two-stage methods

such as Faster R-CNN. This characteristic makes YOLO very suitable for real-time applications and large-scale systems (Jocher & Chaurasia, 2023) (Redmon & Farhadi, 2020).

YOLOv8 is the latest version of the YOLO family developed by Ultralytics with various improvements, such as the use of a more efficient backbone architecture, an anchor-free detection approach, and improved training stability. Recent research has shown that YOLOv8 has superior performance in detecting small and overlapping objects, making it relevant for detecting MBG food components in a single container (Purnomo, 2025) (Ultralytics, 2024).

Openrouter AI

OpenRouter is an Application Programming Interface (API)-based platform that provides centralized access to various large language models from multiple providers through a single endpoint. This platform makes it easy for developers to select and replace models without building separate API integrations for each provider, while also providing routing and fallback mechanisms when the primary model is unavailable or experiencing disruptions. OpenRouter also uses an interface compatible with the OpenAI API format, allowing it to be integrated into Python-based applications via HTTP requests and JSON data exchange. In this study, OpenRouter was used as an intermediary to send a list of YOLOv8n-detected foods to the AI model, which then received responses in the form of estimated energy, protein, carbohydrates, fat, fiber, and nutritional information. With this mechanism, the system can automatically obtain nutritional information without manually maintaining a nutritional database (OpenRouter, n.d.).

Roboflow

Roboflow is a platform used for computer vision dataset management, from data upload, annotation, and augmentation to exporting datasets in formats compatible with various deep learning models, including YOLOv8. In this study, Roboflow was used to assist with the bounding box annotation and data augmentation process to make the dataset more diverse and representative (Nelson, 2022) (Roboflow, 2023).

Using Roboflow makes it easier for researchers to ensure dataset quality, label consistency, and data format compatibility with YOLOv8. With a well-managed dataset, the performance of object detection models can be significantly improved.

Research methods

The system development method used in this study is the Waterfall method, a development method carried out in stages and sequentially, starting from analysis to system evaluation. This method was chosen because it has a systematic and easy-to-understand workflow, making it suitable for the development of an image-based component detection and nutritional estimation system for Free Nutritious Food (MBG) using the YOLOv8 model.

Needs Analysis

A needs analysis was conducted to determine the main components in the development of an image-based MBG food nutrient detection and estimation system. Data requirements include images of food packages with menu variations, lighting, shooting angles, size, shape, and possible object overlap, as well as nutritional data in the form of energy, protein, fat, and carbohydrates. The devices used include a mobile phone camera for image capture and a laptop for system development. YOLOv8 is used as a detection model, while Roboflow is used for annotation, dataset management, and model training. Python and supporting libraries are used in the system implementation to process images and integrate detection results with nutritional information automatically according to the specified research needs.

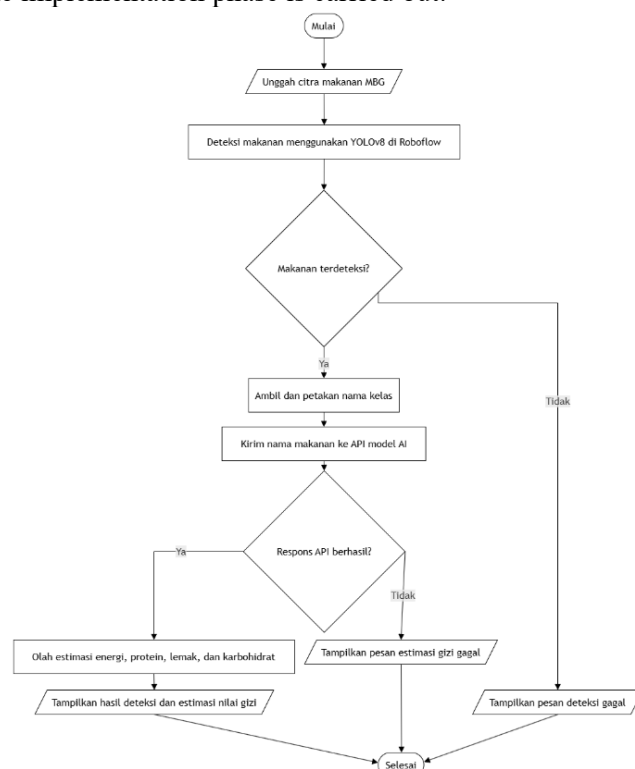
Data collection

Data collection was conducted at the Sumolawang Nutrition Fulfillment Service Unit (SPPG), Mojokerto, by recording MBG food packages before consumption using a mobile phone camera. Recording was done from several angles and lighting conditions that adjusted to field conditions to obtain a variety of object views. Each video was at least 20 seconds long and then extracted into frames evenly with a target of 100 images per class. From approximately 130 extracted frames, selection was

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carried out by removing images that were blurry, too dark, had high similarity, were cropped, or did not display the object completely. The selected images were then used as a dataset for the annotation process, training, validation, and testing of the YOLOv8 model.

System Design

System design is the stage carried out to translate research requirements into a system design for component detection and nutritional estimation of Free Nutritious Food (MBG) based on imagery. The design includes the relationship between users, web applications, YOLOv8 models, Roboflow services, and the AI model API as the main components in the data processing process. This design is designed to ensure that each component can work in an integrated manner, from processing input images to presenting information on detection results and nutritional value estimation. In addition, the system design serves as the basis for determining the process flow and communication mechanisms between components before the implementation phase is carried out.



Picture1. System flowchart

Figure 1 shows the proposed system flow. The system flow begins with the user uploading an MBG food image for processing by the YOLOv8 model. The detection results, in the form of food classes, are then mapped and sent to the AI model's API to obtain energy, protein, fat, and carbohydrate estimates. The system then processes the detection results and nutrient estimates and displays them to the user. If the food or API response is not successfully processed, the system displays a failure message to inform the user.

System Implementation

The system implementation produces a web application to detect MBG food components and display their estimated nutritional content. The system uses Python and Flask as the backend, HTML, CSS, Bootstrap, and JavaScript as the frontend, and YOLOv8n deployed through Roboflow for the detection process. The detection results are processed using OpenCV to display bounding boxes and food labels, then forwarded to the AI model API to obtain energy, protein, fat, and carbohydrate estimates. The implementation includes the main page, image upload, analysis process, and the detection results and nutritional estimation pages.

System Testing

System testing was conducted to ensure all functions in the food detection and nutritional estimation application function as designed. The method used was Black Box Testing, which assesses the suitability between system input and output without discussing the program code structure. Testing was conducted on the main page function, image upload, camera usage, detection process via Roboflow, bounding box visualization, and nutritional content estimation via the OpenRouter API. The test format was structured following the test structure in the comparison document, namely including the function, test scenario, expected results, and test status.

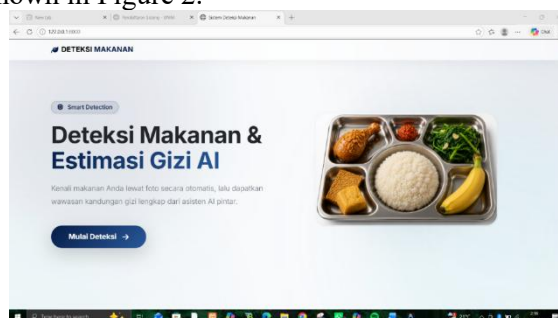
Results and Discussion

System Implementation

The system is implemented in the form of a web application that allows users to independently perform MBG food analysis. Users can access the main page, select an image from their device or take a picture using the camera, and then submit the image for analysis. Once the process is complete, users can view the food component detection results along with nutritional information on the results page. If the image cannot be processed or the object is not successfully recognized, users receive failure information and can upload or take a new image for further analysis. The interaction flow is designed to ensure the system is simple and easy to understand.

Home Page

The homepage is the initial display that appears when users access the MBG food detection web application. This page serves as an introduction, providing brief information about the system's purpose and function before users begin the detection process. The page's interface is designed to be simple and responsive for use on devices with different screen sizes. This design allows users to understand the application's functionality and begin the detection process without complicated steps. The homepage display is shown in Figure 2.

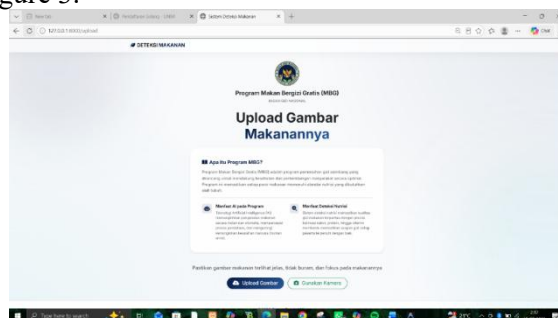


Picture2. Home Page

Upload Image Page

The image upload page is used to enter food images into the system. The main section of the page offers two input options: the Upload Image and Use Camera buttons. Once a file is selected, the system displays a preview of the image so the user can verify the image is correct.

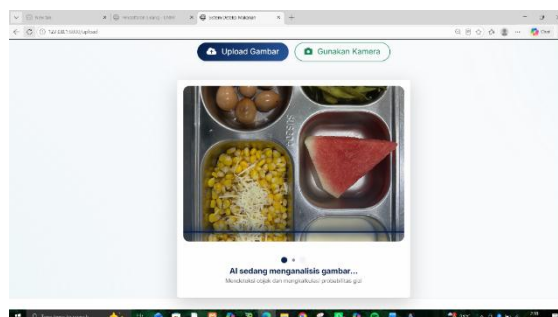
This page also includes instructions regarding recommended image quality. Users are encouraged to use images that are not blurry, have adequate lighting, and clearly display all parts of the food. This is necessary because image quality affects the YOLOv8n model's detection results. The image upload page is shown in Figure 3.



Picture3. Image upload page

Detection Process Page

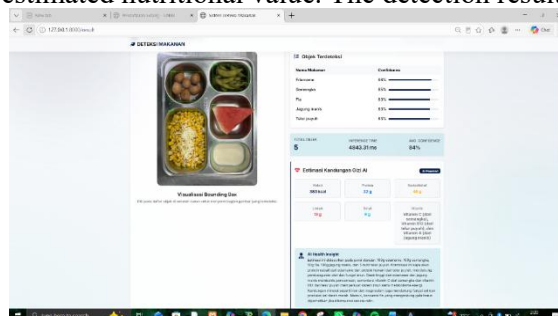
The detection process page appears after the user selects an image using the Upload Image button. At this stage, the system displays the selected image as a preview so the user can verify the accuracy of the processed image. During the process, the page displays an indicator consisting of three dots and the text "AI is analyzing the image." This indicator indicates that the system is communicating with the Roboflow service and awaiting detection results. The detection process page is shown in Figure 4.



Picture4. Detection process page

Detection Results Page

The results page is the final stage after the food image has been processed by the system. On this page, the application displays the object detection results from the YOLOv8n model in Roboflow as well as the nutritional content estimates obtained through the AI model API. The information is organized into sections so users can see the relationship between the detected objects, the model's confidence level, and their estimated nutritional value. The detection results page is shown in Figure 5.



Picture5. Detection results page

System Functionality

The system's functionality includes uploading or capturing food images, image validation, food component detection, and presentation of detection results and nutritional value estimation. The system also provides information on confidence scores, object positions via bounding boxes, a list of detected foods, processing time, and estimates of energy, protein, fat, and carbohydrates. In the event of a detection failure, an invalid image, or a disruption in the nutritional estimation service, the system informs the user and provides the option to re-analyze using a new image. The functional table of this program system is shown in Table 1.

Table1. System functionality table

Function	Testing Scenario	Results
System access	Open the application	The main page appears
Upload image	Choosing food images	Image successfully loaded
Camera	Taking images through the camera	Image captured successfully
Food detection	Processing MBG images	Food components detected
Detection results	Displaying detection results	Name and confidence appear
Nutritional estimates	Processing detection results	Nutritional information is displayed

Detection failed	Using imagery without food	Detection message failed to appear
Estimation failed	Nutrition API is not responding	Failure message appears
Re-detection	Uploading a new image	Previous results updated

System test results

The test results show that the application's main functions can run according to the designed flow, starting from image input, food component detection, result visualization, and nutritional value estimation. In the detection test, the system was able to recognize five objects with an average confidence of 84% and an inference time of approximately 4.84 seconds. The detection results were then successfully forwarded to the API to generate estimates of energy, protein, carbohydrates, fat, and fiber. The test also showed that the system can handle detection failures and API disruptions without stopping the application. Functionally, black box testing shows that the system output is in accordance with predetermined user actions.

Discussion

The results of the study indicate that the YOLOv8n application can be used to detect multiple food components in a single image of a Free Nutritious Food (MBG) package. The system is able to display the object name, bounding box, confidence score, number of objects, and inference time, so that the detection results can be used as a basis for the nutritional value estimation process. In the tests conducted, five objects were successfully detected with an average confidence of 84% and an inference time of approximately 4.84 seconds. These results indicate that the system has been able to carry out the detection process functionally on MBG food images.

Integrating detection results with the AI model API also demonstrated that the system goes beyond object identification and can also retrieve nutritional information from food names. The system successfully displayed estimates of energy, protein, carbohydrates, fat, fiber, and vitamins, as well as health insights. Thus, the approach used in this study connects computer vision processes with nutritional information, transforming food images into more user-friendly nutritional information.

In terms of application reliability, the error handling mechanism also demonstrates that the system can maintain detection results when the nutritional estimation service experiences disruptions. The system provides a backup AI model and continues to display detection results if the nutritional estimation process is unsuccessful. Black-box testing demonstrates that the application's core functions can operate according to user actions, including image input, food detection, result visualization, and nutritional estimation presentation.

Overall, this study demonstrates that integrating YOLOv8 with a nutrition information service has the potential to be a more practical approach to aid component identification and nutritional value estimation of MBG packages. The study's primary contribution lies in combining multi-object food detection with nutritional information presentation in a single web-based application. However, further testing using model evaluation metrics and comparing nutritional estimates with standards or manual calculations is still needed to strengthen the validity of the study's results.

Conclusion

Based on the results of the research and system implementation, it can be concluded that:

1. The YOLOv8n model was successfully implemented to detect food components in image-based Free Nutritious Food (MBG) packages. The system displays object names, bounding boxes, confidence scores, number of objects, and inference time. In testing, five objects were successfully detected with an average confidence level of 84% and an inference time of approximately 4.84 seconds.
2. The integration of detection results with the AI model API was successfully carried out to produce estimated information on energy, protein, carbohydrates, fat, fiber, vitamins, and health explanations of the detected food.
3. Functional testing demonstrated that the system could operate according to the designed flow, from image input, food detection, result visualization, and nutritional information presentation. The system was also able to handle detection failures and API service disruptions without stopping the application.

4. The model's performance cannot yet be fully assessed quantitatively, as precision, recall, and mean average precision (mAP) values are not yet available in the research results. Nutritional estimates are also still based on detected food categories and do not take into account physical measurements of food portions or volumes.
5. Overall, the system shows potential as a tool for monitoring MBG food, particularly for identifying food components and providing integrated nutritional information estimates through a web-based application.

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