Penerapan YOLOv5 untuk Klasifikasi Gambar dalam Sistem Estimasi Kandungan Kalori Masakan Indonesia

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Riwayat Artikel

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Maximus Aurelius Wiranata[#1], Caecilia Citra Lestari[✉#2]

[#] *Program Studi Informatika, Universitas Ciputra Surabaya,*
CitraLand CBD Boulevard, Made, Kec. Sambikerep, Surabaya, 60219, Indonesia

[1]maurelius@student.ciputra.ac.id
[2]caecilia.citra@ciputra.ac.id
[✉]Corresponding author: caecilia.citra@ciputra.ac.id

Abstrak — **Di zaman teknologi yang terus berkembang ini, aplikasi penghitung kalori menjadi sangat penting bagi individu yang peduli akan pola makan dan kesehatan mereka. Namun, sebagian besar aplikasi tersebut belum sepenuhnya dapat mengakomodasi variasi masakan yang umum dikonsumsi di Indonesia, terutama masakan yang populer di Pulau Jawa, yang memiliki jumlah penduduk terbesar di Indonesia. Untuk mengatasi kekurangan ini, penelitian ini memperkenalkan solusi inovatif berupa Sistem Klasifikasi Masakan Indonesia dan Estimasi Kandungan Kalori menggunakan teknologi YOLOv5. Dalam pendekatan ini, teknologi klasifikasi objek YOLOv5 digunakan untuk mengidentifikasi berbagai jenis masakan Indonesia, termasuk delapan kelas seperti sate, bakso, soto, nasi goreng, gado-gado, ayam goreng, rawon, dan rendang. Sistem ini tidak hanya mampu mengklasifikasikan masakan dengan akurat, tetapi juga memberikan estimasi kandungan kalori berdasarkan komposisi bahan makanan yang terklasifikasi. Implementasi dari penelitian ini menggabungkan YOLOv5 untuk menerapkan model klasifikasi masakan Indonesia dengan menggunakan API nutrisi dari API Ninjas untuk mendapatkan data nutrisi yang diperlukan. Penelitian ini menggunakan dataset yang diperoleh dari website Kaggle, Mendeley Data, dan Roboflow, dengan total 303 gambar untuk setiap kelas masakan. Hasilnya, model mencapai skor akurasi sebesar 94,2%, precision sebesar 94,3%, recall sebesar 93,8%, dan F1 Score sebesar 93,8%.**

Kata kunci— **klasifikasi gambar; masakan Indonesia; perhitungan kalori; YOLOv5.**

YOLOv5 Implementation for Image Classification in Indonesian Cuisine Calorie Estimation System

Abstract — ***In this era of continuously evolving technology, calorie counting applications have become crucial for individuals who are concerned about their eating habits and health. However, most of these applications have not fully accommodated the variety of dishes commonly consumed in Indonesia, especially the popular dishes in Java Island, which has the largest population in Indonesia. To address this limitation, this research introduces an innovative solution in the form of an Indonesian Cuisine Classification and Calorie Content Estimation System using YOLOv5 technology. In this approach, the YOLOv5 object classification technology is used to identify various types of Indonesian dishes, including eight classes such as satay, meatball soup, traditional soup, fried rice, mixed vegetables***

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salad, fried chicken, beef soup, and beef stew. This system is not only capable of accurately classifying dishes but also provides calorie content estimation based on the composition of the classified food ingredients. The implementation of this research combines YOLOv5 to apply the Indonesian cuisine classification model using the nutrition API from API Ninjas to obtain the required nutrition data. This research uses datasets obtained from Kaggle website, Mendeley Data, and Roboflow, with a total of 303 images for each class of dishes. As a result, the model achieved an accuracy score of 94.2%, precision of 94.3%, recall of 93.8%, and an F1 Score of 93.8%.

Keywords— ***calorie calculation; image classification; Indonesian cuisine; YOLOv5.***

I. Introduction

Maintaining a healthy diet is an important investment in keeping the body healthy [1]. According to a survey by the American College of Sports Medicine (ACSM), global fitness trends have grown exponentially over the past 15 years [2]. After the COVID-19 pandemic, many people in Indonesia have started adopting a healthy lifestyle to boost immunity, focusing on the importance of maintaining health and choosing a balanced diet [3]. This shift marks progress compared to 2016, when many people were too busy with their activities, leading them to neglect health and food choices [4], [5].

Calorie counting apps have become some of the most popular applications due to their ability to calculate calorie intake. Nearly a third of smartphone users have used a calorie counting app, as it serves as an appealing diet-monitoring tool. With its ability to automatically calculate and recommend daily calories or macronutrient needs based on weight or health-related goals set by the user, it provides valuable support [5]. Its ease of use is enhanced by a feature that allows users to input images of dishes, eliminating the need to type dish names and search manually.

Although there are many apps available that allow users to count calories, there is a lack of data on specific dishes, especially Indonesian cuisine. For example, the Lifesum app, a daily nutrition tracker, does not contain nutritional information for “soto” (accessed in February 2024), which is one of the most common dishes in Indonesia [6]. This forms the primary basis for developing an application focused on Indonesian cuisine.

In previous studies, there has been research on detecting various types of food, including Indonesian dishes with calorie calculations. However, among the 13 types of food used in that study, only three were Indonesian dishes—"ayam goreng” (fried chicken), “tempe goreng” (fried tempeh), and “perkedel kentang” (potato fritters), while the rest were assorted fruits, eggs, and plain rice [7]. This results in a lack of diversity in common Indonesian dishes available for classification, highlighting the need for a calorie counter specifically for Indonesian cuisine.

The choice of YOLOv5 as the image classification algorithm is based on previous research related to Asian food detection, which compared various Convolutional Neural Network (CNN) algorithms for model development. The results indicated that TR-YOLO (YOLOv5-transformer) and YOLOv5 were the two best algorithms, achieving evaluation results of mAP50/% (mean average precision calculated at an intersection over union threshold of 0.50) of 79.60% and 73.85%, respectively [8]. The excellent performance in object detection is one of the reasons for testing YOLOv5 as a model for image classification.

This research aims to develop a calorie-counting application specifically for Indonesian cuisine by leveraging YOLOv5 for food image classification. The purpose is to provide a more accurate, efficient, and user-friendly tool for users to calculate calorie intake from traditional Indonesian dishes. Accuracy is ensured through YOLOv5’s high performance in food detection, allowing precise classification of Indonesian dishes. Efficiency is achieved by automating calorie estimation through image recognition, eliminating the need for manual input. Finally, user-friendliness is emphasized through an intuitive mobile interface, making it accessible for individuals who want to monitor their nutrition with minimal effort.

II. Research Methodologies

The research method used in this study is the waterfall method. This method is known for its clear sequential approach, where each stage of development is carried out consecutively, starting from planning, analysis, design, implementation, testing, to maintenance. It also has very detailed criteria before starting the design phase [9]. This approach allows researchers to have an in-depth understanding of each stage of the development process, as well as enabling systematic evaluation at every step.

Figure 1 is a flowchart of the waterfall method used in this study. The research begins with the first step, which is the concept phase, where the main focus is on identifying the system implementation to be carried out. Once the concept is established, the next step is to define the system requirements in detail during the requirements phase. In this stage, all system needs are carefully studied to ensure that no detail is overlooked. After the system requirements are met, the next phase is design, where a system design is carefully developed to ensure alignment with the previously established needs.

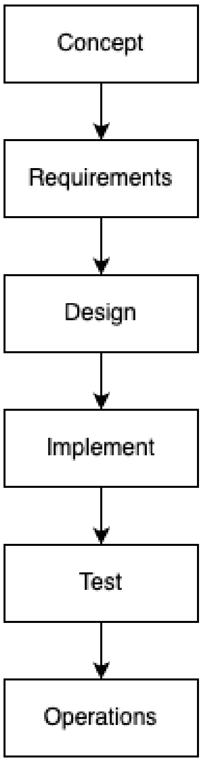

Figure 1. Waterfall Method

After the system design is completed, the implementation phase begins, where the plans developed in the previous stage are brought to reality. This implementation involves building the system based on the design that has been created. Next, after the implementation is completed, the following phase is testing. In this stage, the implemented system will be thoroughly tested to ensure that its performance meets expectations and satisfies all established requirements.

Finally, after going through all the previous stages, the system is ready for operation. This operational phase marks the end of the system development process and allows users to start actively using the system. Thus, from conception to operation, the waterfall methodology approach provides a structured and organized framework for conducting this research, ensuring that each step of the system development process is executed carefully and efficiently.

III. Result and Discussion

The results and discussion of this study analyze the effectiveness of the Indonesian food classification model and nutritional calculation system, highlighting its accuracy, reliability, and discrepancies in nutritional data when compared with other sources. The steps are as follows:

A. Concept

The initial phase of this research involves designing the system concept. Broadly speaking, the system utilizes the YOLOv5 version classify to perform image classification of Indonesian dishes. Among the various YOLOv5 variations available, the one with the highest accuracy is selected. The resulting YOLOv5 model is implemented in the application using an API (Application Programming Interface). To obtain nutritional information, the system uses the Ninjas API and recipes from the Cookpad website. All these components are planned to be integrated into a single application.

B. Requirements

The next step is to establish a list of requirements. These requirements are divided into four sections: dataset requirements, application platform, selection of the YOLOv5 model, and API usage. To determine the types of dishes to be used in this research, the researcher chose to focus on popular dishes from the island of Java. A survey was conducted to identify the most commonly encountered dishes. This survey involved respondents living on the island of Java and asked about the ten dishes they most frequently encounter in their daily lives. A total of 45 respondents participated in the survey. The results of the survey are shown in Figure 2 below.

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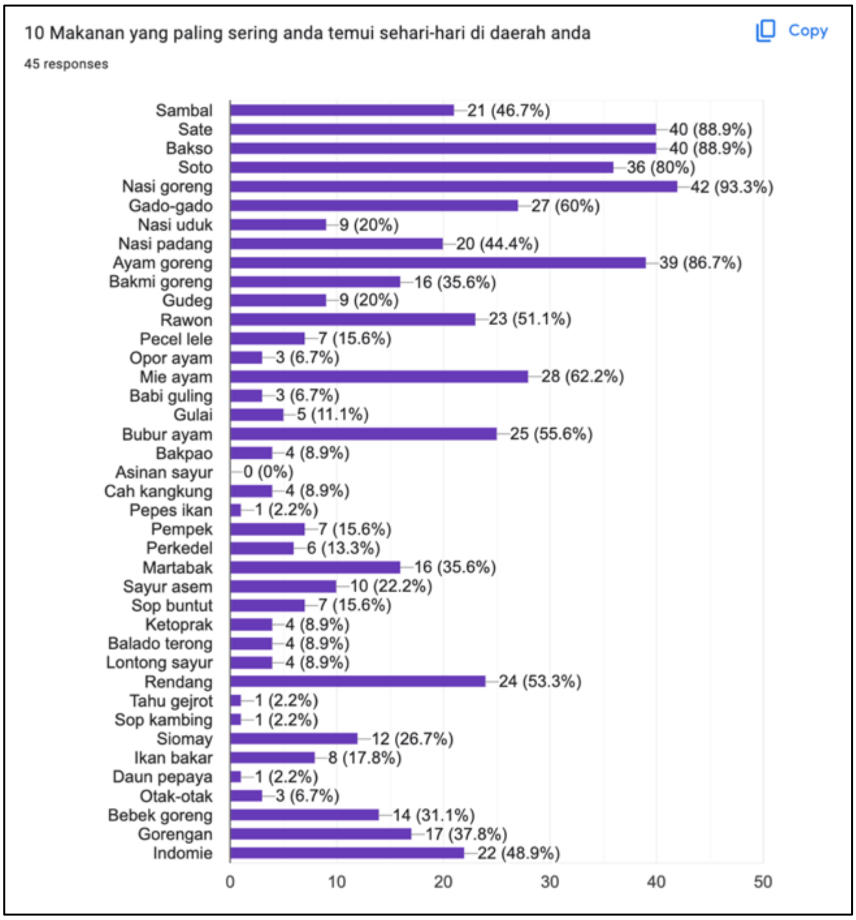

Figure 2. Results of the Survey on Popular Dishes in Java Island

Figure 2 shows the results of the survey conducted using Google Forms. Based on the survey results, the ten dishes most frequently encountered by respondents on the island of Java are satay, meatballs, soto, fried rice, gado-gado, fried chicken, rawon, chicken noodles, chicken porridge, and rendang. For each of these dishes, a dataset will be sought, and the available ones will be established as the list of food datasets used in this research.

The combined dataset consists of images of eight Indonesian dishes: sate (satay), bakso (meatballs), soto, nasi goreng (fried rice), gado-gado, ayam goreng (fried chicken), rawon, and rendang. These images were collected from three sources: Mendeley Data, Kaggle, and Roboflow. Each dataset varies in terms of size, image resolution, and labeling methods.

- Mendeley Data (https://data.mendeley.com/datasets/vtjd68bmwt/1): This dataset includes images of bakso (meatballs), gado-gado, nasi goreng (fried rice), rawon, rendang, sate (satay), and soto.
- Kaggle (https://www.kaggle.com/datasets/faldoae/padangfood): This dataset contains images of ayam goreng (fried chicken) and rendang.
- Roboflow (https://universe.roboflow.com/faldoae/padang-food-image-classification): Similar to the Kaggle dataset, this dataset includes images of ayam goreng (fried chicken) and rendang.

After combining these datasets, duplicate or low-quality images were removed to ensure consistency. The final dataset is balanced across the eight selected dish categories, ensuring that the model learns to classify each class effectively.

Regarding the application platform, the target users for this system are individuals who are highly attentive to nutrition and dietary needs, specifically those belonging to the upper social class [10], [11]. This social class tends to prefer using iOS devices over Android [11]. Therefore, in the implementation of this system, an iOS-based application has been chosen.

The selection of the model was based on top 1 accuracy, which measures the percentage of times the model's highest-confidence prediction matches the correct label in image classification tasks. The top 1 accuracy is calculated using equation (1):

$$Top\ 1\ Accuracy = \frac{Number\ of\ correctly\ classified\ images}{Total\ number\ of\ images}\ x\ 100\% \quad (1)$$

The accuracy results were obtained from the YOLO documentation, where various YOLOv5-cls models, including YOLOv5n-cls, YOLOv5s-cls, YOLOv5m-cls, YOLOv5l-cls, and YOLOv5x-cls, were pre-trained. Table 1 provides a comparison of their top 1 accuracy and inference speed on ONNX CPU.

TABLE 1
YOLOV5 MODELS PERFORMANCE COMPARISON

Model	Top 1 Accuracy	Speed (ONNX CPU)
YOLOv5n-cls	64,6	3,3 ms
YOLOv5s-cls	71,5	6,6 ms
YOLOv5m-cls	75,9	15,5 ms
YOLOv5l-cls	78,0	26,9 ms
YOLOv5x-cls	79,0	54,3 ms

In the comparison, YOLOv5n-cls stands out with the best speed but has the worst accuracy, while YOLOv5x-cls, despite having the worst speed, offers the highest accuracy [12]. In the context of this research, high speed is not the primary priority; instead, a high level of accuracy is emphasized. Since achieving the highest classification accuracy is the main objective, the most suitable model to use in this research is the YOLOv5x-cls version.

To integrate the system with the Indonesian dish image classification model, an API built with Python Flask is used. Additionally, the system is also connected to the API Ninjas, which serves as a tool for retrieving nutritional data.

C. Design

After all requirements have been established, the next step is the design phase. This design is conducted to plan the system architecture that will be implemented. Below is Figure 3, which illustrates the system architecture for this research.

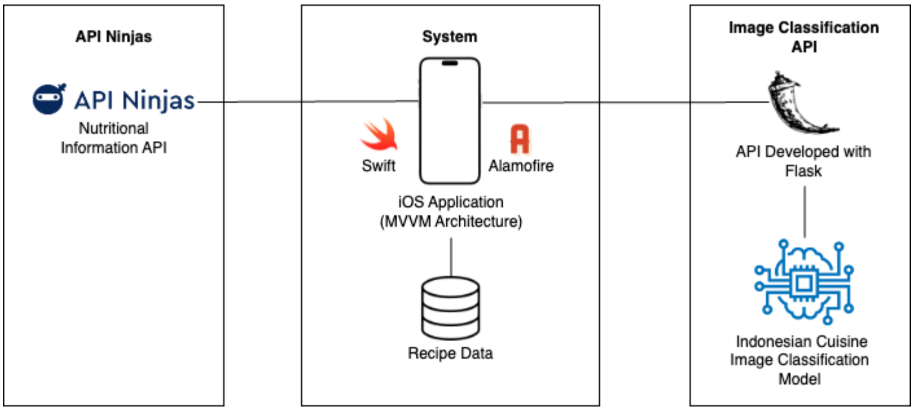

Figure 3. System Architecture Diagram

Figure 3 is the system architecture diagram implemented in this research. In this diagram, there are three objects: API Ninjas, the system, and the image classification API. API Ninjas is the API used to retrieve nutritional data for ingredients from Indonesian dishes. This API is connected to the system that operates within the application. In the system object, there are recipe data files that can be accessed directly without needing to connect to other objects. The application within the system object is built using the Swift programming language and utilizes Alamofire to make requests to the image classification API. In the image classification API object, there is the image classification model for Indonesian dishes, which can be utilized when the system makes a request to this API.

D. Implementation

After completing the design stage, the next step is implementation. This phase begins with the merging of datasets and training the data. The collected datasets are combined and trained using the YOLOv5x-cls model, employing default parameters of a 64 batch size and 10 epochs. The choice of 10 epochs is based on monitoring the training process to determine when the model reaches saturation. In deep learning, saturation occurs when additional training epochs no longer improve the model's accuracy or loss significantly, indicating that the model has learned the patterns in the data as much as possible without overfitting. The results from the model training are shown in Figure 4.

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epoch	train/loss	val/loss	metrics/accuracy_top1	metrics/accuracy_top5	lr/0
0	1.1711	7.2919	0.44262	0.89139	0.000901
1	0.79015	1.4312	0.68443	0.94877	0.000802
2	0.64358	1.0828	0.72746	0.97336	0.000703
3	0.5727	0.85839	0.84221	0.99385	0.000604
4	0.53207	0.6675	0.93443	0.99795	0.000505
5	0.50611	0.66128	0.93033	0.99795	0.000406
6	0.49988	0.64714	0.94262	1	0.000307
7	0.49427	0.64228	0.92623	0.99795	0.000208
8	0.4889	0.64574	0.92418	0.99795	0.000109
9	0.48259	0.64776	0.92828	0.9959	1E-05

Figure 4. Training Results of the Model Using YOLOv5x-cls

The model reached its best top 1 accuracy of 94.2% at epoch 6, meaning it learned the important patterns for classification without overfitting. After this point, training more did not improve accuracy much, showing that the model had learned enough. The precision of 94.3% means most of the model’s predictions were correct, with few mistakes. The recall of 93.8% shows that the model correctly identified most of the actual positive cases. The F1 score of 93.8% confirms a good balance between precision and recall.

These results were influenced by factors like a batch size of 64, a carefully adjusted learning rate, and stopping at 10 epochs to avoid unnecessary training. Because the model achieved an F1 score greater than 90%, it is considered to have strong performance. This makes it a suitable choice for an image classification API using Python Flask, ensuring reliable and accurate predictions.

The image classification model for Indonesian dishes has been successfully implemented. The next step involves the implementation of the iOS application and its integration with the image classification API and the Nutrition API from API Ninjas. This integration will enable users to take advantage of the classification model directly within the app, allowing them to submit images of their dishes and receive nutritional information based on the ingredients detected.

Figure 5 shows the camera page implemented in the iOS application. On this page, users have two options for image input: capturing a photo directly or selecting one from the photo gallery. This design enhances user experience by providing flexibility in how users can submit images of their Indonesian dishes for classification.

Figure 5. Camera Page

Figure 6 displays the results page for classifying Indonesian dishes. This page receives images from the camera page (Figure 5). Upon opening this page, the system calls the Indonesian dish image classification API and retrieves the output, which includes the name of the dish. Users are prompted to enter the number of servings to calculate the nutritional information for the dish. This interactive feature allows users to better understand their caloric intake based on portion sizes, enhancing the application's overall functionality and user engagement.

Figure 6. Classification Result Page

Figure 7 displays the nutritional calculation results page for the dish. Upon opening this page, the system calls the API Ninjas to retrieve nutritional data, including calories, fats, proteins, and carbohydrates. The system utilizes API Ninjas by inputting the ingredients used in the dish, which are stored in a single recipe file. The API returns the nutritional values for each ingredient. Once the system receives the nutritional data for all ingredients, it calculates the total nutritional content by summing up the values from each ingredient, providing users with a comprehensive overview of their meal's nutritional profile. This functionality enhances the user experience by enabling informed dietary choices based on detailed nutritional information.

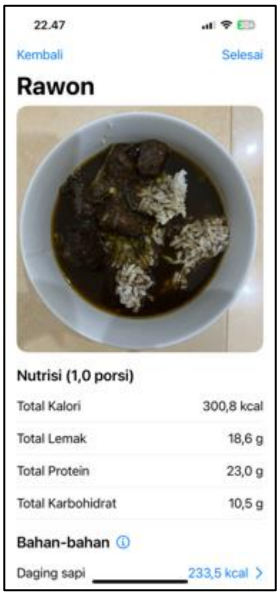

Figure 7. Nutrition Calculation Results Page

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Figure 8 shows the final page, which displays the nutrition per ingredient. On this page, users can select any ingredient from the previous page (Figure 7) to view detailed nutritional information for that specific ingredient. This feature allows users to gain deeper insights into the nutritional content of individual components of their meal, aiding in better dietary planning and understanding of their food choices.

Figure 8. Nutrition per Ingredient Page

E. Test

The next stage after implementing the system is to test the reliability of the system. Two tests were conducted: the dish prediction test and the nutritional test. The dish prediction test was performed using one photo for each class, with a total of eight photos. Table 2 below are the results of the dish prediction test:

TABLE 2
INDONESIAN CUISINE PREDICTION TEST RESULTS

Picture	Actual Label	Prediction Result
	Ayam goreng	Ayam goreng
	Bakso	Bakso
	Gado-gado	Gado-gado

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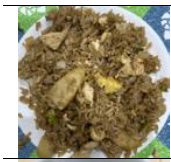
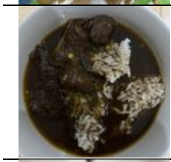
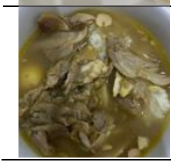
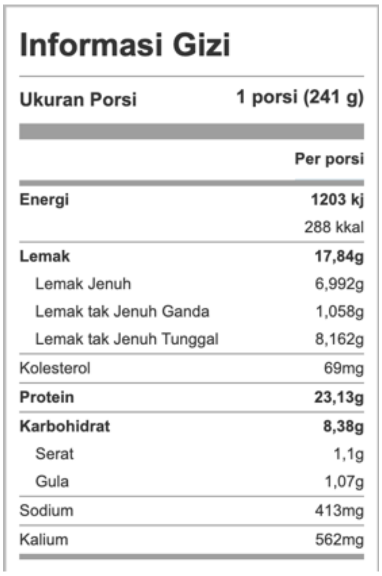
Picture	Actual Label	Prediction Result
	Nasi goreng	Nasi goreng
	Rawon	Rawon
	Rendang	Ayam Goreng
	Sate	Sate
	Soto	Soto

Table 2 shows the results of the Indonesian dish prediction test. Out of eight classes, there was only one class, which is rendang, that was incorrectly predicted as ayam goreng. This indicates that in real-world testing, the system achieved an accuracy of 87.5%.

The nutritional results for rawon in this system, as shown in Figure 9, are 300.8 kcal of calories, 18.6 grams of fat, 23 grams of protein, and 10.5 grams of carbohydrates. These results are slightly higher compared to the nutritional results for rawon from the FatSecret website, which include 288 kcal of calories, 17.84 grams of fat, 23.13 grams of protein, and 8.38 grams of carbohydrates [13]. Although there are minor differences, this indicates that the nutritional calculations from the system are fairly accurate in providing nutritional information for rawon.



Informasi Gizi

Ukuran Porsi	1 porsi (241 g)
	Per porsi
Energi	1203 kj
	288 kkal
Lemak	17,84g
Lemak Jenuh	6,992g
Lemak tak Jenuh Ganda	1,058g
Lemak tak Jenuh Tunggal	8,162g
Kolesterol	69mg
Protein	23,13g
Karbohidrat	8,38g
Serat	1,1g
Gula	1,07g
Sodium	413mg
Kalium	562mg

Figure 9. Nutritional Information for Rawon from FatSecret

In the testing with another dish, namely sate, the system displayed the nutritional calculations for one serving of sate, as shown in Figure 10. The results are 674.5 kcal of calories, 37.7 grams of fat, 54.7 grams of protein, and 41.1 grams of carbohydrates. There is a significant difference compared to the nutritional results for sate from the FatSecret website, as shown in the image. Those results include 225 kcal of calories, 14.82 grams of fat, 19.54 grams of protein, and 4.87 grams of carbohydrates [14]. This difference is due to the varying portion sizes, where FatSecret uses a size of 100 grams, while this system uses 200 grams of chicken, not including spices and other additional ingredients.

Informasi Gizi

Ukuran Porsi	100 gram (g)
	Per porsi
Energi	**943 kj**
	225 kkal
Lemak	**14,82g**
Lemak Jenuh	3,429g
Lemak tak Jenuh Ganda	3,874g
Lemak tak Jenuh Tunggal	6,418g
Kolesterol	49mg
Protein	**19,54g**
Karbohidrat	**4,87g**
Serat	1,9g
Gula	1,99g
Sodium	355mg
Kalium	315mg

Figure 10. Nutritional Information for Sate from FatSecret

F. Operation

The operational stage marks the final phase, where the system has been fully implemented and thoroughly tested. As a result, the system is now prepared for effective use by users. Feedback from users indicated a high level of satisfaction, as the image classification proved to be accurate, correctly identifying various Indonesian dishes. Additionally, users appreciated the app's ability to provide detailed nutritional information for each ingredient, making it a valuable tool for those who want to track their dietary intake.

IV. CONCLUSION

The model achieved strong classification performance with an accuracy of 94.2%, precision of 94.3%, recall of 93.8%, and an F1 score of 93.8%, indicating effective feature extraction and minimal misclassifications. These results were influenced by high-quality training data, well-tuned hyperparameters, and the capabilities of the YOLOv5x-cls model. Minor gaps between precision and recall suggest occasional misclassifications, likely due to class overlapping features. Additionally, the application successfully utilized the Ninjas API, which sourced its ingredients from Cookpad recipes, to retrieve nutritional data based on dish ingredients. In real-world testing across eight trials, the system achieved 87.5% accuracy, correctly classifying seven cases while misclassifying rendang as ayam goreng. However, variations in serving sizes caused differences in nutritional content between the Ninjas API data and the FatSecret nutrition website, highlighting a limitation in standardizing nutritional information.

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REFERENCES

[1] Dhienalight and C. C. Lestari, "Rancang Bangun Sistem Rekomendasi Makanan Alternatif Berkalori Lebih Rendah Berbasis Konten Menggunakan Hierarchical Clustering," Teknika, vol. 9, no. 2, pp. 88–96, 2020.

[2] V. M. Kercher et al., "Fitness Trends From Around the Globe," ACSMs Health Fit J, vol. 25, pp. 20–30, 2020.

[3] A. M. Fernandito and R. M. Ritonga, "Analisis Pengaruh Penerapan Gaya Hidup Sehat Terhadap Minat Mengkonsumsi Makanan Sehat Pada Yellow Fit Kitchen," Jurnal Sosial dan Teknologi (SOSTECH), pp. 613–619, 2023.

[4] T. E. R. Nursalim and T. Wiradinata, "Analisis Jalur Pengaruh Kepercayaan Konsumen Dan Desain Website Terhadap Minat Beli Ulang, Dengan E- Commerce Sebagai Variabel Intervening: Studi Kasus Pada Produk E'chick Secara Online," Jurnal Performa: Jurnal Manajemen dan Start-Up Bisnis, vol. 1, no. 1, 2016.

[5] M. Messer, Z. McClure, B. Norton, M. Smart, and J. Linardon, "Using an app to count calories: Motives, perceptions, and connections to thinness- and muscularity-oriented disordered eating," Eat Behav, vol. 43, 2021.

[6] "Lifesum: Healthy diet plan." [Online]. Available: https://apps.apple.com/us/app/lifesum-healthy-diet-plan/id286906691

[7] F. Romadhon et al., "Food Image Detection System and Calorie Content Estimation Using Yolo to Control Calorie Intake in the Body," E3S Web of Conferences, vol. 465, p. 2057, 2023.

[8] X. Tan and X. He, "Improved Asian food object detection algorithm based on YOLOv5," in E3S Web of Conferences, EDP Sciences, 2022.

[9] A. M. Dima, M. A. Maassen, and M. Alexandra, "From Waterfall to Agile software: Development models in the IT sector, 2006 to 2018. Impacts on company management," Journal of International Studies, pp. 315–325, 2018.

[10] R. Jin, T.-T. Le, R. T. Villarino, A. Mazenda, M.-H. Nguyen, and Q.-H. Vuong, "How social classes and health considerations in food consumption affect food price concerns," 2023.

[11] R. M. Siburian and R. P. Nuary, "The Difference of IoS and Android Usage," Jurnal Darma Agung, vol. XXVII, no. 2, pp. 1057–1062, 2019.

[12] "ultralytics/yolov5: YOLOv5." [Online]. Available: https://github.com/ultralytics/yolov5

[13] "Kalori Dalam Rawon (1 Porsi) Dan Fakta Gizi." [Online]. Available: https://www.fatsecret.co.id/kalori-gizi/umum/rawon?portionid=8730600&portionamount=1,000

[14] "Kalori Dalam Sate Ayam (100 Gram) Dan Fakta Gizi." [Online]. Available: https://www.fatsecret.co.id/kalori-gizi/umum/sate-ayam?portionid=4969313&portionamount=100,000