Journal of Applied Science, Technology & Humanities
Volume 3, Issue 3, June, 2026, Pages 1168-1184

ISSN 3032-5765
DOI: https://doi.org/10.62535/w4wdnq37

Journal of Applied Science Technology & Humanities

Integration of ResNet50 Architecture in Food Image Detection Systems for Dynamic Nutrition Estimation

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The development of modern lifestyles demands accurate food intake management to maintain health quality. This study aims to assess NutriScan, an online tool for identifying the type of citra and calculating calories automatically. The AICrowd Food Recognition Challenge dataset is used for quantitative modeling utilizing the Convolutional Neural Network (CNN) ResNet50 architecture based on transfer learning, and nutritional data is integrated via Application Programming Interface (API). Data augmentation, cropping, scaling, and normalization are used in the processing of Citra. According to the study's findings, NutriScan has the potential to be an effective and adaptable web-based solution with an accuracy of roughly 75%, precision of 76%, recall of 75%, and F1-score of 75%.

Keywords: Food Image Recognition, CNN ResNet50, Transfer Learning, Nutritional Analysis, Web-Based System.

INTRODUCTION

The health of modern society is closely correlated with food consumption patterns and daily lifestyle (Shen *et al*., 2020; Udayana & Nugraha, 2020; Yunus *et al*., 2019). Failure to maintain a balanced daily nutritional composition not only reduces immunity but also increases the risk of various chronic and degenerative health disorders (Komalyna, 2025; Quan *et a*l., 2025; Sesar Husen Santosa *et al*., 2024a; Shen *et al*., 2020; Yunus *et al*., 2019). This situation demands an accurate intake monitoring mechanism, both for individuals maintaining fitness and those undergoing weight management programs (Harel, 2025; Saad *et al*., 2025; Shen *et al*., 2020). Despite increasing public awareness of lifestyle habits, calorie recording methods that require users to manually search for and enter nutritional data are prone to estimation errors (Komalyna, 2025; Saputra, 2025). With advances in artificial intelligence technology, computer vision approaches offer potential solutions for automating food image recognition (Bamatraf *et al*., 2025; Cohen *et al*., 2022; Hidayat *et al*., 2024; Lestari *et al*., 2020; R. A. Putri *et al*., 2024; Rahmani *et al*., n.d.; Theodore Armand *et al*., 2024; Vianda *et al*., 2025). Through a supervised learning paradigm, systems are trained to recognize complex visual patterns from thousands of labeled food images, enabling machines to adopt human-like visual perception capabilities (Asmoro & Solichin, 2024; Irawan, 2024; Jenie *et al*., 2021; Saputri *et al*., 2024). However, implementation on a web platform requires an architecture that is able to balance analysis speed and detection accuracy without burdening computing resources (Azani *et al*., 2025; Ekawati *et al*., 2025; Heleen, 2025; Siskandar *et al*., 2020, 2023).

Previous studies, such as (M. E. Putri *et al*., 2024) and (Shafa & Andono, 2025), adopted the Mask Region-based Convolutional Neural Network (Mask R-CNN) algorithm to segment food objects. This method has proven superior in separating objects down to the pixel level, providing very sharp image boundary precision (Quan *et al*., 2025; Talaat *et al*., 2024). However, the complexity of the Mask R-CNN network structure requires massive memory allocation and processing power, often resulting in less than ideal latency for web-based applications (M. E. Putri *et al*., 2024). As a lighter alternative, (Riswanto *et al.*, 2024) implemented the Single Shot Multibox Detector (SSD) method that prioritizes detection speed, in line with the approach (Darma Udayana & Nugraha, 2020) which utilizes a pure Convolutional Neural Network (CNN) for visual classification. Although both methods offer improved processing time efficiency, the calorie estimation mechanisms offered are still static because they rely entirely on local databases or manual reference tables embedded in the system. This limitation causes the system to be rigid and unable to automatically update nutritional information (Komalyna, 2025). Beyond the purely visual approach, Optical Character Recognition (OCR) techniques were also tested by (Sonita, 2018) but its application was limited to reading text on packaging labels and failed to identify visual features of prepared foods that lack written information (Fauzi, 2025).

Based on this gap analysis, there is an urgency to develop a system that is not only reliable in visual feature extraction but also integrated with dynamic nutritional data (Santosa *et al*., n.d.; Wiyoto et al., 2022). This study aims to design NutriScan, a web-based system that adopts a Convolutional Neural Network (CNN) architecture with a ResNet50 model (Irawan, 2024; Wasilah *et al*., 2025). CNN was chosen for its ability to extract features while preserving spatial information of the image, to ensure the model is able to recognize food image datasets in various serving conditions through pre-processing stages, including pixel matrix normalization and data augmentation (Elpeltagy & Sallam, 2021; Liu *et al*., 2025; Shen *et al*., 2024; Wan *et al*., 2024). This process aims to enrich the variety of training data and prevent overfitting (Dede Husen, 2024). The ResNet50 architecture was chosen based on a residual learning mechanism that utilizes skip connections, thus addressing accuracy degradation in deep networks and the vanishing gradient problem (Bohlol *et al*., 2025; Rathi *et al*., 2020; Wen *et al*., 2020; Wu *et al*., 2019, 2019). ResNet50 is a ResNet architecture with 50 pre-trained layers (Berliani *et al*., 2023a). These characteristics enable the model to learn complex visual features of food with higher accuracy compared to previous models such as VGG16, while maintaining less computational efficiency compared to full-pixel segmentation-based models (Behar & Shrivastava, 2022; Mascarenhas & Agarwal, 2021; Sari *et al*., 2025; Targ *et al*., 2016; Theckedath & Sedamkar, 2020a, 2020b; Wu *et al*., 2019).

The novelty of this research lies in the end-to-end system integration that connects visual classification with an external nutrition database drawn from the Kaggle dataset. In the NutriScan architecture, ResNet50 is tasked with predicting food class labels from uploaded images with the highest probability. These predicted labels then act as keywords that are automatically sent by the system through direct integration with the nutrition dataset. This mechanism allows the system to dynamically extract the latest calorie and macronutrient data, unlike previous studies that separate the detection process from calorie calculation. By implementing a stepwise classification pipeline from binary to multiclass based on ResNet50, this study evaluates the model's effectiveness in addressing class imbalance problems and complex differences in food category characteristics (Ambar *et al*., 2025). Furthermore, the use of a model with a relatively small number of parameters such as ResNet50 shows that problems in simple multimodal models can be effectively solved without the need for complex architectures or high computational requirements (Leong & Zhao, 2025). This approach is expected to eliminate manual input processes and produce health monitoring instruments that are responsive, accurate, and adaptive to user needs (Santosa *et al*., 2021; Siskandar, Santosa, *et al*., 2022a).

METHODS

Location and Time of Research

The research was conducted at the Vocational School of IPB University, Kumbang Street No. 14, RT.02/RW.06, Babakan, Middle Bogor District, Bogor City, West Java 16128, Indonesia, for three months, starting from March 2025 to May 2025. The research stages include problem identification, dataset collection, pre-processing, ResNet50 model training, and implementation on the NutriScan web platform. This systematic stage structure is important to ensure that each phase of deep learning model development is well documented and accountable (Berliani *et al*., 2023b).

Method of collecting data

The research used was modeling and experimental research with a quantitative approach. The use of experimental methods in developing the CNN model allowed researchers to test various parameters to achieve the optimal level of accuracy (R. A. Putri *et al*., 2024). The data collected was secondary data obtained through documentation studies in public data repositories (Kusumah *et al*., 2021).

The datasets used were the AI Crowd Food Recognition Challenge image dataset, containing thousands of food images for classification purposes, and the Calories in Food Items (per 100 grams) nutrition dataset, which served as a reference database for calculating calorie estimates based on detected food labels. The integration of these two data sources resulted in a comprehensive nutritional information system (Azani *et al*., 2025; Darma Udayana & Nugraha, 2020).

Data Analysis Methods

Data analysis is a systematic process to identify problems and needs as a basis for determining appropriate solutions (Andre *et al*., 2020; Ariq Mayangkara *et al*., 2024; Pangesti *et al*., 2022; Wahyudiningsih *et al*., 2022; Yoridho *et al*., 2020). This study uses a deep learning approach with a convolutional neural network (CNN) architecture to classify food types and estimate their calorie content. CNN was chosen because of its highly effective ability to automatically extract visual features from complex image data (Ikasari *et al*., 2025; Kusumo, 2024; Vianda *et al*., 2025). This research process was carried out systematically through several main stages, including data preparation, data preprocessing & augmentation, CNN model development, training, and evaluation. The overall research workflow can be seen in Figure 1.

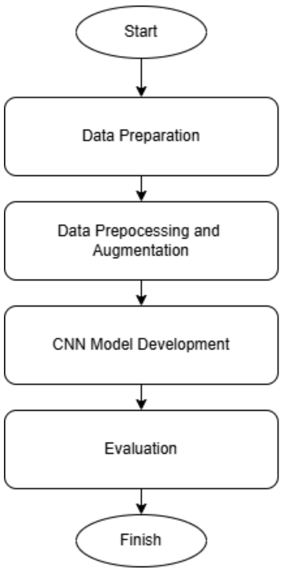

Figure 1. Research workflow

Data Preparation

The data used in this study consists of two main dataset sources integrated to achieve classification and estimation objectives. The first dataset is the AICrowd Food Recognition Challenge, which provides thousands of labeled food images for training computer vision capabilities. The second dataset is Calories in Food Items (per 100 grams), which is used as a reference database for nutritional values. The selection of these two datasets was based on the completeness of the variety of food types and the validity of the available nutritional data, ensuring consistency between image recognition results and calorie calculations.

The image dataset is divided into two main parts training data and validation data (Hossain *et al*., 2022; Peryanto *et al*., 2020). Training data is used to train the model to recognize food texture, shape, and color patterns, while test data is used to evaluate the model's performance on previously unseen data to avoid overfitting (Budi *et al*., 2024; Mahaputri *et al*., 2022; Tian & Chen, 2019; Zidni & Akbar, 2024). In this study, the data was divided with a proportion of 80% for training data and 20% for testing data to ensure the model has sufficient data to learn and be properly validated (Kusumo & Aditya, 2024). The selection of this dataset is based on data validity to ensure consistency between image recognition and reference nutritional values, similar to the importance of validity testing in the implementation of appropriate technology (Elinah *et al.*, 2025).

Data Prepocessing dan Augmentation

Data preprocessing is a crucial step to ensure the image is in a standard and optimal format before being processed by the CNN architecture (Muntarti *et al*., 2025). The first step involves localization and cropping based on a bounding box to focus the model on the main food object and reduce background noise (You *et al*., 2023). Next, the image is resized to a square shape to conform to the standard ResNet50 input layer. The final preprocessing step is the use of the resnet_preprocess_input function, which aims to standardize the image pixel values to match the distribution of the pre-trained model parameters.

The next step is to apply data augmentation techniques, including rotation, shifting, zooming, shearing, flipping, and brightness adjustments (Bohlol *et al*., 2025; Farhan, 2024; Sutarti & Fariza Syaqialloh, 2025). The goal of this technique is to overcome the limited amount of data for a particular class and improve the model's generalization ability. Data augmentation is a key strategy to prevent models from simply memorizing data (memorization) instead of learning general features (Al-Fahrezi, 2025; Islam *et al*., 2022). Furthermore, brightness adjustments are made to simulate various lighting conditions when photographing real-world food. This augmentation technique helps enrich the dataset, and the model is expected to remain accurate even when the food objects are photographed from different angles or under different lighting conditions (Dede Husen, 2024b).

Convolutional Neural Network Model Development

The model development in this study used Python with TensorFlow and Keras as the core libraries. The chosen architecture was ResNet50, which utilizes residual learning mechanisms to address the vanishing gradient problem in deep neural networks (Muzhaffar & Suharjo, 2025). The approach used was transfer learning, where the ResNet50 model used weights pre-trained on the ImageNet dataset (weights='imagenet') (Pratiwi & Nudin, 2024; Purba *et al*., 2017). This strategy effectively accelerated training time and improved performance on relatively smaller datasets compared to ImageNet (Wasilah *et al*., 2025b).

The original top layer of ResNet50 was removed (include_top=False) and replaced with a custom classification head tailored for food classification in NutriScan, consisting of a GlobalAveragePooling2D layer, a Dense layer with 256 units and ReLU activation, a BatchNormalization layer, a Dropout layer with a rate of 0.5 to prevent overfitting (Tian & Chen, 2019). The final Dense layer with softmax activation corresponding to 13 output classes (apple, banana, bread-white, broccoli, carrot, cheese, coffee-with-caffeine, egg, french-beans, pasta-spaghetti, rice, sweet-potato, and tea). The full base model layers were frozen (layer.trainable = False), allowing ResNet50 to function purely as a feature extractor without updating the pre-trained ImageNet weights. The model was compiled using the Adam optimizer with a learning rate of 0.001 and CategoricalCrossentropy loss with label smoothing of 0.1, with a batch size of 16 and input image size of 224×224 pixels. Training was conducted on a total of 6,813 training images and 355 validation images for 50 epochs on a CPU runtime via Google Colab, with two callbacks applied: ModelCheckpoint to save the best model based on validation accuracy, and EarlyStopping to halt training when validation performance ceased to improve.

Training

In the training phase of a convolutional neural network (CNN) model, the model is trained using a fit method utilizing an augmented data generator (Mochammad Toyib *et al*., 2024; Solihin *et al*., 2022). Training runs for 50 epochs with a batch size adjusted to the device's memory capacity. Model parameter optimization is performed using the Adam (Adaptive Moment Estimation) optimizer with a learning rate of 1e-4, chosen for its ability to adaptively adjust the learning rate and maintain stable weight updates during the training process (Banerjee *et al*., 2024). During the training process, model performance is monitored in real time to ensure the system's effectiveness in producing accurate output (Santi *et al*., 2024; Sesar Husen Santosa *et al*., 2024b). This training is monitored through accuracy and loss metrics on both training and validation data.

This training process aims to gradually optimize the model's internal parameters, namely weights and biases, to reduce the difference between the model's predictions and the actual labels. The entire training history is stored in a history variable for further analysis. Fluctuations in the accuracy and loss graphs during this stage serve as a reference for researchers to fine-tune model parameters if indications of underfitting or overfitting are found (Sasongko *et al*., 2023).

Evaluation

The evaluation phase is carried out by analyzing the accuracy and loss graphs generated during the training process (Burhanuddin *et al*., 2025; Triloka & Mutiara, 2025). These graphs provide an overview of the model's ability to learn from the data and the resulting error rate. In addition to monitoring standard metrics, testing is conducted using a confusion matrix to identify which food classes are most accurately predicted and which classes are frequently misclassified. System success is measured by significant performance improvements after the training process (Ariq Mayangkara *et al*., 2024; Siskandar *et al*., 2025).

Once the model reaches an accuracy level deemed optimal, it is saved in .h5 or .keras format. The model is then integrated into the NutriScan web platform using the Flask framework. During this implementation phase, the food image classification results from the ResNet50 model are linked to a calorie database to automatically display total calorie estimates to users (Jenie *et al*., 2021). Web-based implementation ensures that nutrition applications can be widely accessed by users through any device (Azani *et al*., 2025; Kharismatunnisaa *et al*., 2023).

RESULTS AND DISCUSSION

This chapter presents the results of testing a food image detection system and calculating nutritional information using a Convolutional Neural Network (CNN) to evaluate the performance of the NutriScan web system in recognizing food types and detecting nutritional information per 100 grams. The following are the test results.

Evaluation Metrics

Evaluation metrics were used to assess the performance of the Convolutional Neural Network (CNN) model developed for food classification (Pratama & Fajri, 2025). The evaluation was conducted using four main metrics: Accuracy, Precision, Recall, and F1-Score (Estian Pambudi *et al*., 2025; Helmiyah & Pramestiawan, 2025). To evaluate the effectiveness of the selected architecture, a comparative experiment was conducted between MobileNetV2 and ResNet50 trained on the same dataset and preprocessing pipeline. The results are summarized in Table 1.

Table 1 Comparison of Model Performance Between Architectures

Model	Epoch	Accuracy	Precision	Recall	F1-Score
MobileNetV2	50	76%	0.76	0.76	0.76

ResNet50	50	75%	0.76	0.75	0.75

Based on Table 1, MobileNetV2 achieved a slightly higher accuracy of 76% compared to ResNet50 at 75%. However, ResNet50 was selected as the final architecture for NutriScan due to its deeper residual learning mechanism, which provides stronger feature representation for complex food visual patterns and proven stability across a larger number of training epochs. The marginal 1% accuracy difference does not outweigh the architectural advantage of ResNet50 in terms of robustness and generalization, particularly for a multiclass food classification task with class imbalance as observed in this study. A detailed summary of the ResNet50 model performance is presented in Figure 2.

	precision	recall	f1-score	support
apple	0.88	0.92	0.90	38
banana	0.81	0.89	0.85	28
bread-white	0.97	0.88	0.92	65
broccoli	0.60	0.55	0.57	11
carrot	0.61	0.72	0.66	39
cheese	0.50	0.45	0.48	22
coffee-with-caffeine	0.81	0.93	0.87	42
egg	0.64	0.53	0.58	30
french-beans	1.00	0.43	0.60	7
pasta-spaghetti	1.00	0.78	0.88	9
rice	0.49	0.62	0.55	29
sweet-potato	0.40	0.33	0.36	6
tea	0.88	0.72	0.79	29
accuracy			0.75	355
macro avg	0.74	0.67	0.69	355
weighted avg	0.76	0.75	0.75	355

Figure 2. Summary of performance evaluation results of the mode

Based on Figure 2, the developed CNN model achieved an accuracy of 75%, indicating that 75% of the total test data was correctly classified. This accuracy value reflects the model's overall performance in recognizing various food classes. The weighted average precision value was 76%, indicating that most of the model's predictions for a class were correct. A relatively high precision indicates that the model has a relatively low rate of false positive predictions. Furthermore, the weighted average recall value of 75% indicates the model's ability to correctly retrieve data for each class. A recall value comparable to accuracy indicates that the model was able to recognize most of the food samples available in the test data. The weighted average F1-score value obtained was 75%, which is the harmonic mean between precision and recall. These results indicate that the model has a good balance between prediction accuracy and the ability to detect all data in each class. Overall, the evaluation results indicate that the model has stable performance in classifying food types.

Training and Validation Data Accuracy

Based on the results of the model training conducted and explained in the method, the training data accuracy was 78.9%, while the validation data accuracy was 75%. The increase in accuracy values on the training data followed by relatively close validation accuracy values indicates that the model is able to learn visual food patterns quite well and has adequate generalization capabilities to data that has not been seen before. The difference in accuracy values between the training and validation data indicates a tendency for mild overfitting, but still within acceptable limits for a web-based classification system. One factor influencing this difference in performance is the imbalance in the amount of data between classes, as shown in Figure 3.

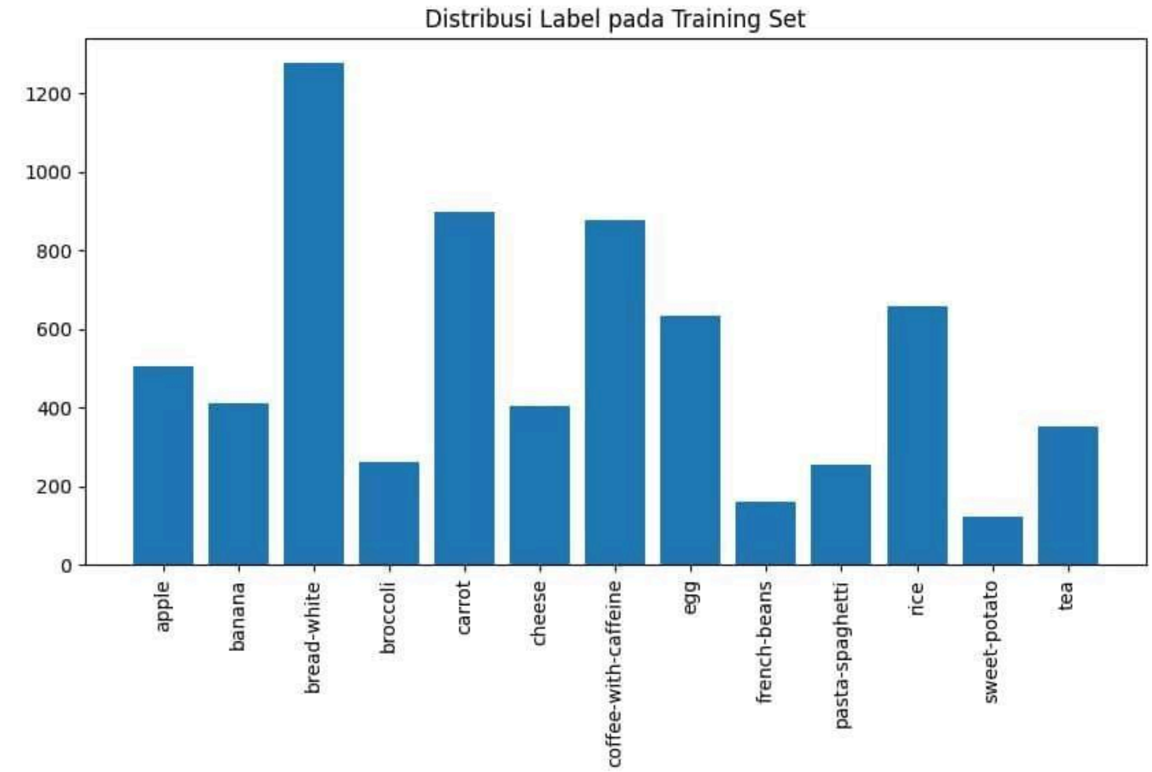

Figure 3. Imbalance in the amount of data between classes

In Figure 3, the label distribution graph for the training data shows that some classes, such as bread-white, carrot, and coffee-with-caffeine, have significantly larger data sets than other classes, such as sweet-potato and french-beans. This imbalance in data distribution could potentially cause the model to perform better at recognizing classes with large data sets, while performing lower on classes with limited data sets. Nevertheless, the training results show that the model maintained fairly stable performance overall.

Prediction Test

Prediction testing was conducted using validation data not used in the model training phase. The purpose of this testing was to evaluate the ability of a Convolutional Neural Network (CNN) model with the ResNet50 architecture to classify food types in greater detail within each class. The results of the prediction testing are visualized using a confusion matrix, as shown in Figure 4.

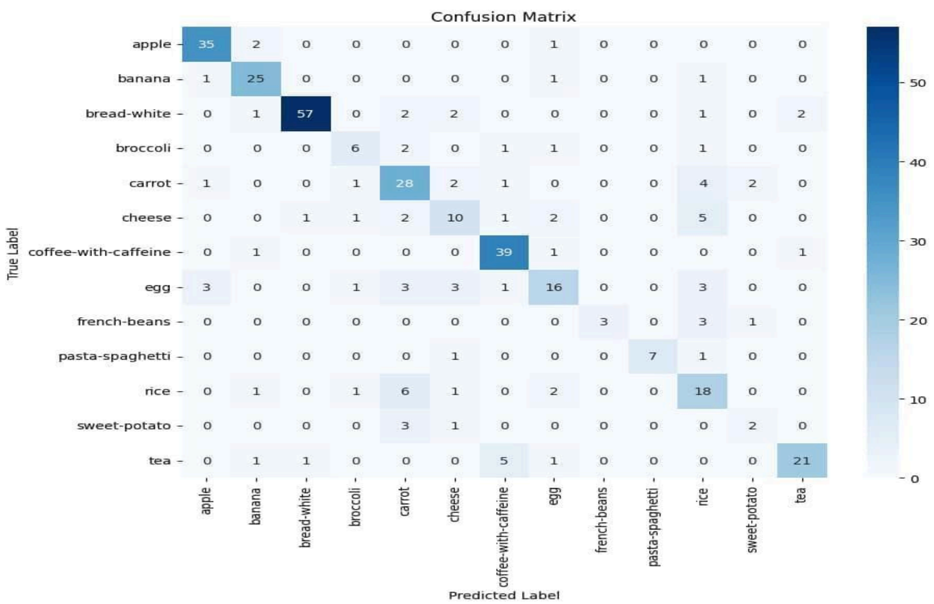

Figure 4. The results of the prediction test

Figure 4 shows that the majority of correct predictions are distributed along the main diagonal of the confusion matrix, indicating that the model is able to correctly classify most food images. Several food classes, such as apple, white bread, and coffee with caffeine, demonstrate good prediction performance, characterized by a high number of correct predictions and relatively low misclassifications. This is due to the clear and consistent visual characteristics of these classes.

Conversely, some food classes, such as sweet potato and French beans, show lower numbers of correct predictions. Misclassification errors in these classes are influenced by the limited data size and visual similarities between food types. Nevertheless, the prediction test results indicate that the ResNet50 model is capable of providing fairly good classification performance for most food classes.

System Implementation on the NutriScan Website

Implementation of the NutriScan system on a website demonstrated that the trained food classification model performed well in real-world scenarios (Siskandar, Wiyoto, *et al*., 2022). The system was able to accept user-uploaded images and automatically display detection results in the form of food names, confidence scores, and estimated calories per 100 grams based on available nutritional data, as shown in Figures 5, 6, and 7.

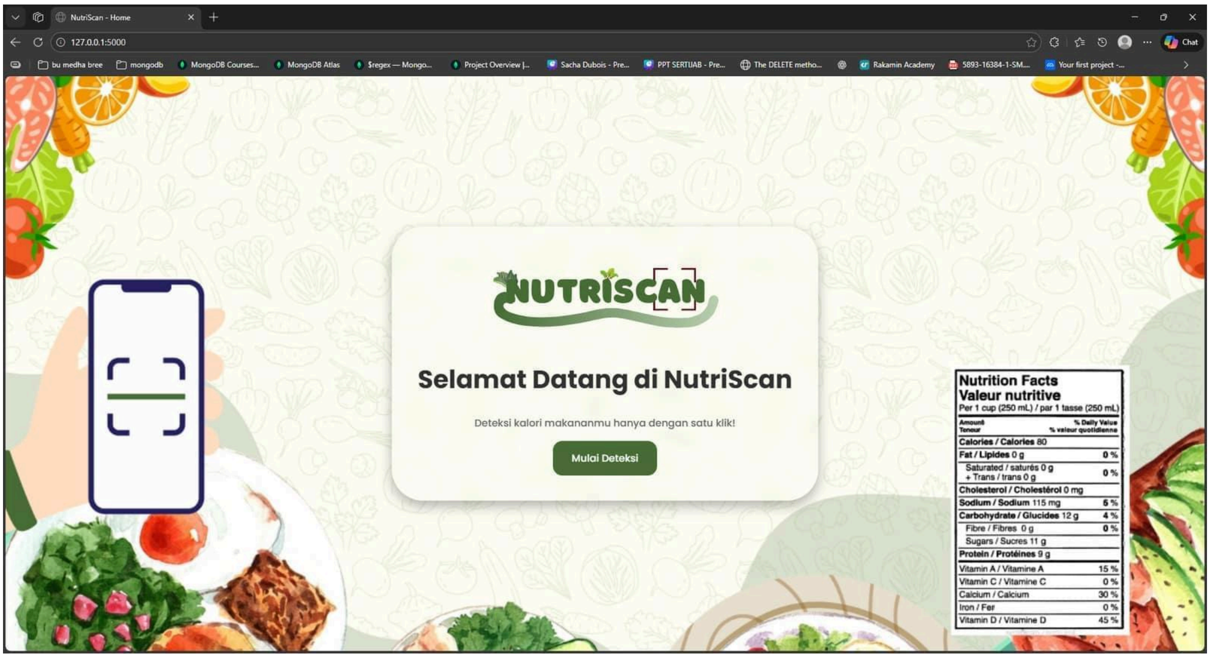

Figure 5. Front page view of the NutriScan website

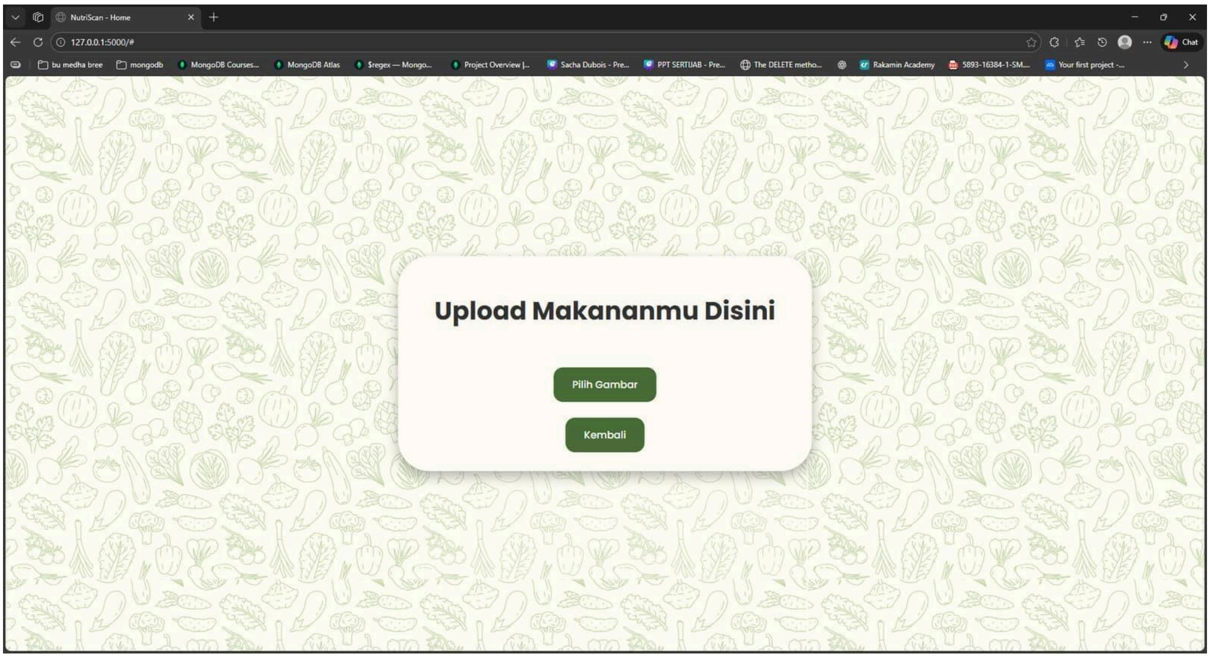

Figure 6. Food upload page view

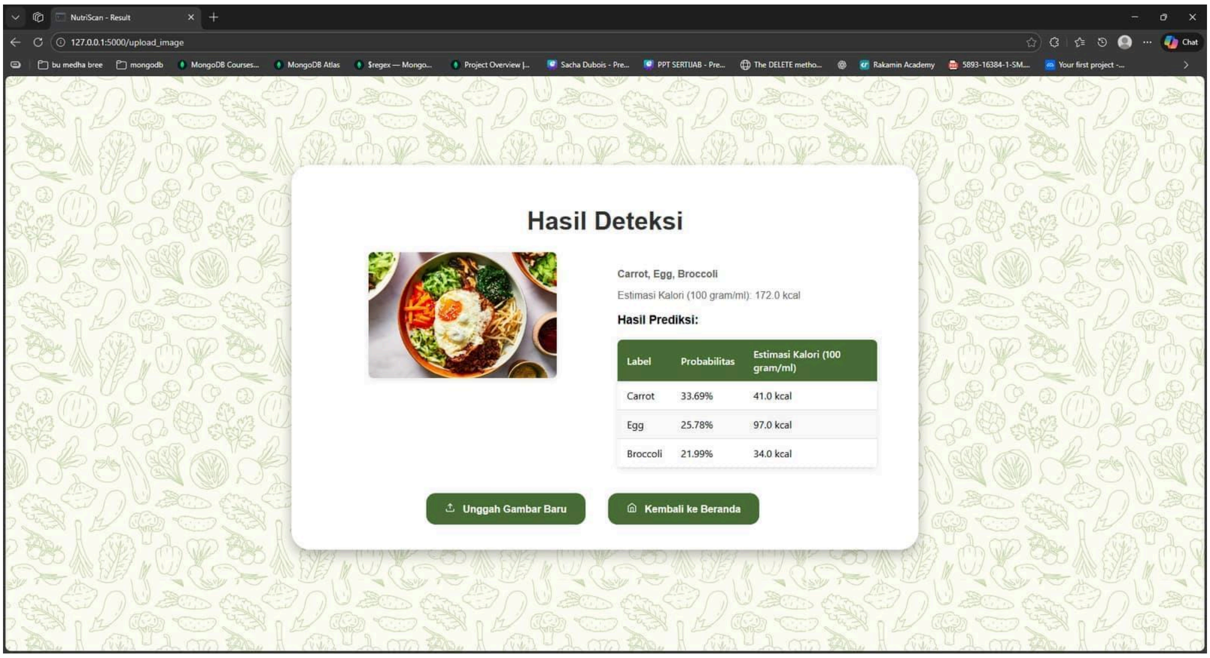

Figure 7. Food detection results page view

Based on Figures 5, 6, and 7, it can be seen that after the user uploads a food image, the system immediately displays the classification results along with the calorie estimate on the same page without requiring any additional interaction. The test results demonstrate that the system can display information consistently and responsively, making it easier for users to obtain calorie estimates for the food they consume.

Furthermore, the system was also tested under conditions where the uploaded image was not a food item or did not fall into a class recognized by the model. In these conditions, the system would not display any images identified as food and would not display the calorie estimate, as shown in Figure 8. This mechanism aims to prevent misinterpretation of the results and increase the reliability of the information provided to users.

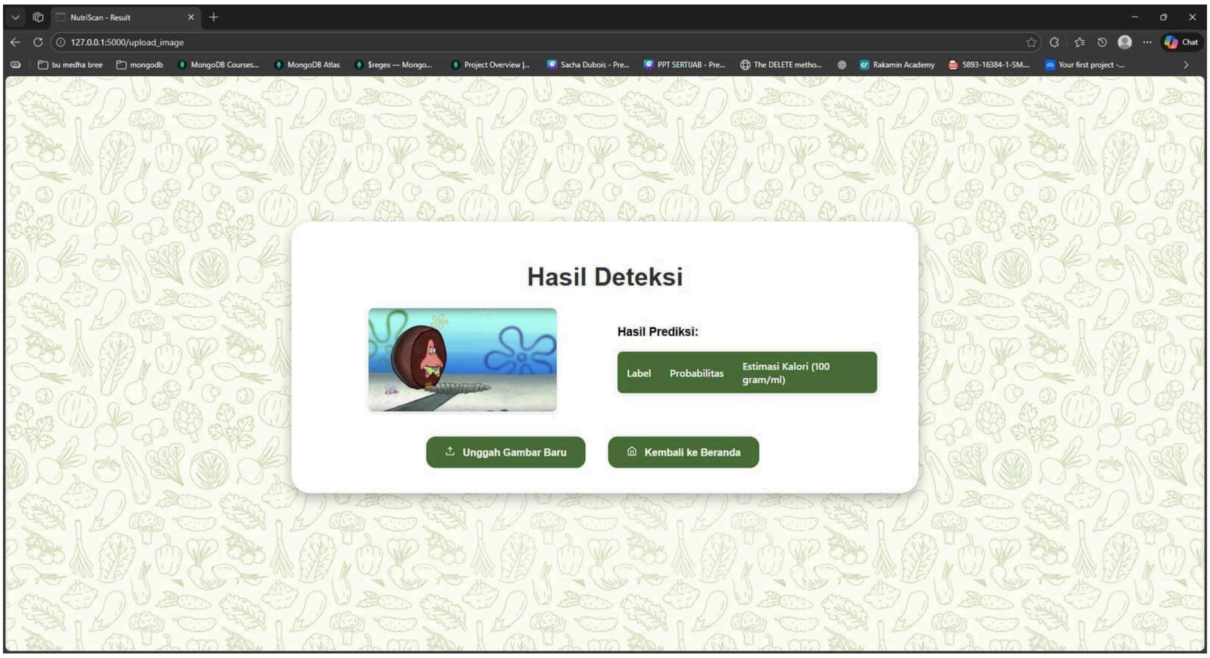

Figure 8. The result of the uploaded image detection is not food

Thus overall, the results of the NutriScan website implementation prove that the system is capable of functioning as an end-to-end system for automatic food type recognition and calorie estimation, and has a mechanism for handling invalid input to support a better user experience (Siskandar, Santosa, *et al*., 2022).

CONCLUSION

This study successfully developed NutriScan, a web-based food image detection system integrating the ResNet50 CNN architecture with dynamic nutritional data retrieval. With an accuracy of 75%, precision of 76%, recall of 75%, and F1-score of 75%, the transfer learning-based ResNet50 demonstrated stable classification performance across 13 food classes, offering a computational advantage over previous studies that rely on static calorie tables. Nevertheless, this study has several limitations, including the restricted number of food classes, the inability to perform multi-food detection, the absence of actual portion size estimation, and limited testing under variable lighting conditions. Future research is recommended to expand the food class coverage, integrate multi-object detection frameworks such as YOLO, adopt advanced architectures such as EfficientNet or Vision Transformer (ViT), and incorporate depth-based volume estimation for more accurate calorie calculation.

REFERENCES

Al-Fahrezi, M. A. (2025). Pengaruh Augmentasi Data Terhadap Akurasi Pelatihan Model CNN untuk Klasifikasi Jenis Ikan. *JITSI : Jurnal Ilmiah Teknologi Sistem Informasi*, *6*(2), 177–185. https://doi.org/10.62527/jitsi.6.2.471

Ambar, M. K., Öztoprak, H., & Yurtkan, K. (2025). Optimizing ResNet-50 for Multiclass Classification: A Multi-Stage Learning Approach. *IEEE Access*, *13*, 142517–142534. https://doi.org/10.1109/ACCESS.2025.3597227

Andre, D. J., Triwisesa, E., & Siskandar, R. (2020). Rancang Bangun Alat Monitoring Keadaan Air Danau Berbasis Arduino Terintegrasi Web di Limnologi LIPI (Bag. 106-112). *Indonesian Journal of Science*, *1*(2). http://journal.pusatsains.com/index.php/jsi

Ariq Mayangkara, M., Hidayat, D., Tigranaufal Nugraha, I., Dwi Rachmat, R., Riyanti, A., Rodhiyatun nisa, A., Jane putri, E., Fedrianingsih, D., Jesica, M., & Siskandar, R. (2024).

Temperature and Humidity Monitoring Tool Using the Blynk Application for Room Comfort. *Jurnal Sains Indonesia*, *5*(3), 143–154. https://doi.org/10.59897/jsi.v5i3.213

Asmoro, P. B., & Solichin, A. (2024). Penerapan Metode Convolutional Neural Network Untuk Klasifkasi Kualitas Daging Sapi Pada Aplikasi Berbasis Android. *Faktor Exacta*, *16*(4). https://doi.org/10.30998/faktorexacta.v16i4.19564

Azani, S. N., Taib, E. N., Zahara, N., & Rahmawati, L. (2025). Efektivitas Aplikasi Gizi Gen Berbasis Website Dalam Pembelajaran Mata Kuliah Gizi dan Kesehatan. *5*(1), 25–43. https://doi.org/10.25299/baej.2025.22836

Bamatraf, L., Akbar, R., Rahman, Z., Afifah, B., & Nurkholis, N. (2025). Developing a Supply Chain Management Application for Laying Hens with Integrated Egg Quality Detection Based on Computer Vision (Case Study of a Laying Hen MSME): Pengembangan Aplikasi Manajemen Rantai Pasok untuk Ayam Petelur dengan Deteksi Kualitas Telur Terintegrasi Berbasis Penglihatan Komputer (Studi Kasus Usaha Mikro, Kecil, dan Menengah (UMKM) Ayam Petelur). *Indonesian Journal of Innovation Studies*, *27*(1). https://doi.org/10.21070/ijins.v27i1.1873

Banerjee, S., Palsani, D., & Mondal, A. C. (2024). Nutritional Content Detection Using Vision Transformers- An Intelligent Approach. *International Journal of Innovative Research in Engineering and Management*, *11*(6), 21–27. https://doi.org/10.55524/ijirem.2024.11.6.3

Behar, N., & Shrivastava, M. (2022). ResNet50-Based Effective Model for Breast Cancer Classification Using Histopathology Images. *Computer Modeling in Engineering & Sciences*, *130*(2), 823–839. https://doi.org/10.32604/cmes.2022.017030

Berliani, T., Rahardja, E., & Septiana, L. (2023a). Perbandingan Kemampuan Klasifikasi Citra X-ray Paru-paru menggunakan Transfer Learning ResNet-50 dan VGG-16. *Journal of Medicine and Health*, *5*(2), 123–135. https://doi.org/10.28932/jmh.v5i2.6116

Berliani, T., Rahardja, E., & Septiana, L. (2023b). Perbandingan Kemampuan Klasifikasi Citra X-ray Paru-paru menggunakan Transfer Learning ResNet-50 dan VGG-16. *Journal of Medicine and Health*, *5*(2), 123–135. https://doi.org/10.28932/jmh.v5i2.6116

Bohlol, P., Hosseinpour, S., & Soltani Firouz, M. (2025). Improved food recognition using a refined ResNet50 architecture with improved fully connected layers. *Current Research in Food Science*, *10*, 101005. https://doi.org/10.1016/j.crfs.2025.101005

Budi, E. S., Chan, A. N., Alda, P. P., & Idris, M. A. F. (2024). Optimasi Model Machine Learning untuk Klasifikasi dan Prediksi Citra Menggunakan Algoritma Convolutional Neural Network. *4*(5).

Burhanuddin, M. I., Syaifullah, A., Jaya, S. A. P., & Gabriel, M. (2025). Analisis Komparatif Model MobilenetV1 Dan EfficientnetB0 Dalam Klasifikasi Citra Empat Musim Menggunakan Transfer Learning. *Jurnal Teknik Informatika*, *5*(2).

Cohen, A. R., Chen, G., Berger, E. M., Warrier, S., Lan, G., Grubert, E., Dellaert, F., & Chen, Y. (2022). Dynamically Controlled Environment Agriculture: Integrating Machine Learning and Mechanistic and Physiological Models for Sustainable Food Cultivation. *ACS ES&T Engineering*, *2*(1), 3–19. https://doi.org/10.1021/acsestengg.1c00269

Darma Udayana, I. P. A. E., & Nugraha, P. G. S. C. (2020a). Prediksi Citra Makanan Menggunakan Convolutional Neural Network untuk Menentukan Besaran Kalori Makanan. *Jurnal Teknologi Informasi dan Komputer*, *6*(1). https://doi.org/10.36002/jutik.v6i1.1001

Darma Udayana, I. P. A. E., & Nugraha, P. G. S. C. (2020b). Prediksi Citra Makanan Menggunakan Convolutional Neural Network Untuk Menentukan Besaran Kalori Makanan. *Jurnal Teknologi Informasi dan Komputer*, *6*(1). https://doi.org/10.36002/jutik.v6i1.1001

Dede Husen. (2024a). Evaluasi Teknik Augmentasi Data Untuk Klasifikasi Tumor Otak Menggunakan Cnn pada Citra Mri. *TEKNIMEDIA: Teknologi Informasi dan Multimedia*, *5*(2). https://doi.org/10.46764/teknimedia.v5i2.220

Dede Husen. (2024b). Evaluasi Teknik Augmentasi Data Untuk Klasifikasi Tumor Otak Menggunakan Cnn Pada Citra Mri. *TEKNIMEDIA: Teknologi Informasi dan Multimedia*, *5*(2). https://doi.org/10.46764/teknimedia.v5i2.220

Ekawati, N., Kusumah, B. R., Pengestuti, D. D., Rizki, M., Cintia, C., Mutmainah, I., Ali, M. S., Molinda, M., Kiswanto, A., Novanti, T., & Siskandar, R. (2025). Implementasi Teknologi Tepat Guna Pengontrol Kekeruhan Air Hydrosense Untuk Optimalisasi Akuakultur Bumdes: Sebuah Model Pemberdayaan Kolaboratif Karang Taruna dan Bumdes di Desa Pakapasan Girang. *04*.

Elinah, E., Kusumah, B. R., Ruspendi, R., Rizky, R., Hawa, P., Aufaa, M. I. A., Rizki, M., Martin, M., Nuha, U., & Siskandar, R. (2025). Implementasi Teknologi E-Ox Level pada Mitra Sasaran Pokdakan ke Tiga di Wilayah Kabupaten Cirebon, Guna Membantu Permasalahan Dalam Aspek Manajemen Usaha dan Peningkatan Kapasitas Produksi. *Jurnal Abdi Insani*, *12*(3), 883–894. https://doi.org/10.29303/abdiinsani.v12i3.2167

Elpeltagy, M., & Sallam, H. (2021). Automatic prediction of COVID− 19 from chest images using modified ResNet50. *Multimedia Tools and Applications*, *80*(17), 26451–26463. https://doi.org/10.1007/s11042-021-10783-6

Estian Pambudi, R., Purnomo, H., & Aglasia, A. (2025). Analisis Klasifikasi Sentimen Pengguna MyPertamina Menggunakan Metode Evaluasi Precision, Recall, dan F1-Score. *Aisyah Journal of Informatics and Electrical Engineering*, *7*(2). https://jti.aisyahuniversity.ac.id/index.php/AJIEE

Farhan, M. (2024). Klasifikasi Pada Citra Biji Kopi Arabica Hasil Roasting Menggunakan Metode Convolutional Neural Network (cnn) Resnet50v2. *Universitas Islam Negeri Maulana Malik Ibrahim.*

Fauzi, M. R. (2025). Fitur Machine Learning Untuk Mengidentifikasi Kandungan Gula pada Makanan: Studi Kasus Aplikasi Glucofit Untuk Pencegahan Diabetes di Indonesia. *Universitas Islam Indonesia.*

Harel, M. (2025). Pengembangan Aplikasi Android Dengan Integrasi Ai Untuk Monitoring Konsumsi Gula Harian. *2025*. dspace.uii.ac.id/123456789/56680

Heleen, B. (2025). Towards Efficient, Accurate, and Scalable Food Dish Recognition. *SSRN*. https://doi.org/10.2139/ssrn.5048386

Helmiyah, S., & Pramestiawan, R. (2025). Analisis Komparatif Algoritma Machine Learning dengan Metrik Akurasi, Presisi, Recall, dan F1-Score pada Dataset Kacang Kering. *6*(3).

Hidayat, A., Ash-Shiddiq, F. S., Amalya, F., & Gunadarma, U. (2024). Pengembangan Aplikasi Klasifikasi Makanan Dengan Metode Transfer Learning Menggunakan MobilenetV2 dan Integrasi Api Nutrisi Berbasis Web. *Journal Of Social Science Research*, *4*(6), 2397–2419.

Hossain, Md. B., Iqbal, S. M. H. S., Islam, Md. M., Akhtar, Md. N., & Sarker, I. H. (2022). Transfer learning with fine-tuned deep CNN ResNet50 model for classifying COVID-19 from chest X-ray images. *Informatics in Medicine Unlocked*, *30*, 100916. https://doi.org/10.1016/j.imu.2022.100916

Ikasari, I. H., Rosyani, P., & Amalia, R. (2025). Klasifikasi Jenis Buah Menggunakan Metode Cnn. *RIGGS: Journal of Artificial Intelligence and Digital Business*, *4*(2), 5451–5458. https://doi.org/10.31004/riggs.v4i2.1271

Irawan, P. N. C. (2024). Implementasi Deep Learning Menggunakan Algoritma Convolutional Neural Network (Cnn) Dalam Klasifikasi Gambar Makanan Untuk Menentukan Kandungan Kalori pada Makanan. *Sekolah Tinggi Teknologi Terpadu Nurul Fikri*. https://repository.nurulfikri.ac.id/id/eprint/696

Islam, W., Jones, M., Faiz, R., Sadeghipour, N., Qiu, Y., & Zheng, B. (2022). Improving Performance of Breast Lesion Classification Using a ResNet50 Model Optimized with a Novel Attention Mechanism. *Tomography*, *8*(5), 2411–2425. https://doi.org/10.3390/tomography8050200

Jenie, R. P., Suryana, Y., Pambudi, S., Widayanti, T., Irzaman, Nurdin, N. M., Dahrul, M., Iskandar, J., Kurniawan, A., Siskandar, R., Aridarma, A., Rahayu, M. S. K., Riadhie, T. S., & Alatas, H.

(2021). General protocol for ethical conforming development for non-invasive blood biomarker measurement optical device. 050023. https://doi.org/10.1063/5.0037469

Kharismatunnisaa, F., Saputra, Y., Bahri, S., & Siskandar, R. (2023). Penerapan Framework Laravel Pada Modul Profil untuk Website Dinas Cipta Karya, Tata Ruang dan Pertanahan (DCKTRP). *Jurnal Sains Indonesia*, *4*(3), 249–263. https://doi.org/10.59897/jsi.v4i3.175

Komalyna, I. N. T. (2025). Rancangan Aplikasi Tele-Konseling Gizi Berbasis Kecerdasan Buatan Studi Kasus Telenutri Health. *Jurnal Teknologi Konseptual Desain*, *2*(3), 327–355.

Kusumah, B. R., Jaya, A. K., Siskandar, R., & Rahim, F. F. (2021). E-Ox Level: Sustainability Test of Data Storage System and Performance Test on Closed System Fish Pond. *Aquacultura Indonesiana*, *23*(1), 1. https://doi.org/10.21534/ai.v23i1.267

Kusumo, W. P., & Aditya, C. S. K. (2024). Klasifikasi Citra Makanan Berdasarkan Asal Daerah Menggunakan Convolutional Neural Network. *Techno.Com*, *23*(1), 87–95. https://doi.org/10.62411/tc.v23i1.9735

Leong, W. Y., & Zhao, C. H. (2025). Optimisation Solutions and Simple Innovative Solution Research on ResNet50 Model. *ASM Science Journal*, *20*(1), 1–9. https://doi.org/10.32802/asmscj.2025.2002

Lestari, H., Setiawan, W., & Siskandar, R. (2020). Science Literacy Ability of Elementary Students Through Nature of Science-based Learning with the Utilization of the Ministry of Education and Culture's "Learning House." *Jurnal Penelitian Pendidikan IPA*, *6*(2), 215–220. https://doi.org/10.29303/jppipa.v6i2.410

Liu, D., Zuo, E., Wang, D., He, L., Dong, L., & Lu, X. (2025). Deep Learning in Food Image Recognition: A Comprehensive Review. *Applied Sciences*, *15*(14), 7626. https://doi.org/10.3390/app15147626

Mahaputri, C., Kristian, Y., & Setyati, E. (2022). Pengenalan Makanan Tradisional Indonesia Beserta Bahan-bahannya dengan Memanfaatkan DCNN Transfer Learning. *Journal of Intelligent System and Computation*, *4*(2), 61–68. https://doi.org/10.52985/insyst.v4i2.252

Mascarenhas, S., & Agarwal, M. (2021). A comparison between VGG16, VGG19 and ResNet50 architecture frameworks for Image Classification. *2021 International Conference on Disruptive Technologies for Multi-Disciplinary Research and Applications (CENTCON)*, 96–99. https://doi.org/10.1109/CENTCON52345.2021.9687944

Mochammad Toyib, Tegar Decky Kurniawan Pratama, & Ibnu Aqil. (2024). Penerapan Algoritma CNN Untuk Mendeteksi Tulisan Tangan Angka Romawi dengan Augmentasi Data. *Algoritma : Jurnal Matematika, Ilmu pengetahuan Alam, Kebumian dan Angkasa*, *2*(3), 108–120. https://doi.org/10.62383/algoritma.v2i3.69

Muntarti, Y., Alfi Zahra Muharramah, Fiqrah Idhul Dwi, Yabrina Angelika Rantelili, & Ilham Julian Effendi. (2025). Klasifikasi citra asap kebakaran hutan untuk monitoring lingkungan berbasis CNN. *INFOTECH : Jurnal Informatika & Teknologi*, *6*(2), 117–130. https://doi.org/10.37373/infotech.v6i2.1645

Muzhaffar, R., & Suharjo, I. (2025). Penerapan CNN Berbasis Arsitektur ResNet-50 untuk Klasifikasi Citra Mikroskopik Beras Organik dan Anorganik. *5*(2). https://jurnal.pustakagalerimandiri.co.id/index.php/pustakadata

Pangesti, R. A. N., Salsabila, C. S., Wahyudiningsih, N. T., Halim, G., Nugraha, J., Firdaus, M. A. A., Roihan, M., Hizbul, M. L., Kusumah, B. R., & Siskandar, R. (2022). Rancang Bangun Sistem Notifikasi Tepat Guna Sebagai Solusi Langkah Cepat Penanganan Kebakaran. *3*(2).

Peryanto, A., Yudhana, A., & Umar, R. (2020). Klasifikasi Citra Menggunakan Convolutional Neural Network dan K Fold Cross Validation. *Journal of Applied Informatics and Computing*, *4*(1), 45–51. https://doi.org/10.30871/jaic.v4i1.2017

Pratiwi, M. I., & Nudin, S. R. (2024). Pengembangan Sistem Deteksi Dini Kebakaran Menggunakan Pendekatan Transfer Learning dengan Model ResNet50 Berbasis Website.

Purba, G. E. P., Wijoyo, S. H., & Setiawan, N. Y. (2017). Pengaruh Transfer Learning Resnet dan Densenet Terhadap Performa Klasifikasi Ekspresi Wajah Menggunakan Dataset Fer-2013. *1*(1).

Putri, M. E., Khairi, M., Furqan, M., Yusman, B., Jadid, U. N., & Hasan, U. H. Z. (2024a). Deteksi Objek Untuk Menghitung Perkiraan Kalori Makanan Menggunakan Metode R-CNN Mask Berbasis Web. *Jurnal Kecerdasan Buatan,Komputasi dan Teknologi Informasi*, *5*(1). https://ejournal.unuja.ac.id/index.php/core

Putri, M. E., Khairi, M., Furqan, M., Yusman, B., Jadid, U. N., & Hasan, U. H. Z. (2024b). Deteksi Objek Untuk Menghitung Perkiraan Kalori Makanan Menggunakan Metode R-CNN Mask Berbasis Web.

Putri, R. A., Suryadi Satyawan, A., Prihantono, J. A., Linggi, R. S., Paramita, I. G. A. P. S., Iswarawati, N. K. E., Akbar, F., & Utomo, P. A. (2024). Model Deep Learning Untuk Klasifikasi Objek Pada Gambar Fisheye. *Jurnal Teknologi Informasi dan Ilmu Komputer*, *11*(3), 519–528. https://doi.org/10.25126/jtiik.938047

Quan, W., Zhou, J., Wang, J., Huang, J., & Du, L. (2025). Machine Learning-Driven Precision Nutrition: A Paradigm Evolution in Dietary Assessment and Intervention. *Nutrients*, *18*(1), 45. https://doi.org/10.3390/nu18010045

Rahmani, D. P., Wirastuti, M. A., Fakhiratunisa, N., Fauzan, M. F., Suhada, V. R., Fitriani, M. F. D., Falah, N. A., Balle, J. L., Rizha, T., & Siskandar, R. (t.t.). Pembuatan motion graphic iklan aplikasi FlickApp dan Silvi+ di PT Kreigan Sentral Teknologi. *2*(1), 59–69.

Rathi, P., Kuwar Gupta, R., Agarwal, S., & Shukla, A. (2020). Sign Language Recognition Using ResNet50 Deep Neural Network Architecture. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3545064

Riswanto, R., Ahmad, A., Hazriani, H., & Tribuana, D. (2024). Deteksi Kalori Makanan Tradisional Indonesia Menggunakan Metode Single Shot Multibox Detector (SSD): Calorie Detection of Traditional Indonesian Food Using the Single Shot Multibox Detector (SSD) Method. *MALCOM: Indonesian Journal of Machine Learning and Computer Science*, *4*(3), 819–829. https://doi.org/10.57152/malcom.v4i3.1332

Saad, A. M., Rahi, Md. R. H., Islam, Md. M., & Rabbani, G. (2025). Diet Engine: A real-time food nutrition assistant system for personalized dietary guidance. *Food Chemistry Advances*, *7*, 100978. https://doi.org/10.1016/j.focha.2025.100978

Santi, M. A., Har, N. P., Jenie, R. P., Siskandar, R., Syafutra, H., Pratama, E., Negara, T. P., Setiawan, A. A., Alatas, H., & Irzaman. (2024). Effect of Cupric-Doped $SrTiO_3$ Films on Optical Properties Using Spectrophotometry Method. *IOP Conference Series: Earth and Environmental Science*, *1359*(1), 012015. https://doi.org/10.1088/1755-1315/1359/1/012015

Santosa, S. H., Hidayat, A. P., & Siskandar, R. (2021). SAFEA application design on determining the optimal order quantity of chicken eggs based on fuzzy logic. *IAES International Journal of Artificial Intelligence (IJ-AI)*, *10*(4), 858. https://doi.org/10.11591/ijai.v10.i4.pp858-871

Santosa, S. H., Hidayat, A. P., Siskandar, R., & Rizkiriani, A. (t.t.). Milled Cassava Production Capacity Model Through Machine Effectiveness Analysis.

Saputra, F. (2025). Aplikasi Mobile Berbasis Artificial Intelligence Untuk Analisis Gizi Ibu Hamil Dan Rekomendasi Resep Sehat Pencegah Stunting. *Jurnal Kelitbangan*, 2354–5704. http://journalbalitbangdalampung.org

Saputri, B. R. D., Asmawati, F. D., Rahmawati, A., Manggala, I. H., & Hidayattullah, M. F. (2024). Deteksi Bahan Makanan Untuk Rekomendasi Resep Masakan pada Program Diet Menggunakan Algoritma Cnn. *Jurnal ilmiah infotmatika*, *9*(2).

Sari, C. A., Pradana, L. H. S., & Rachmawanto, E. H. (2025). Identifikasi Citra Jenis Rempah-Rempah Menggunakan Arsitektur RestNet50. *June 2025*, *2*(1), 27–41. https://doi.org/10.28918/logiclink.v2i1.10713

Sasongko, T. B., Haryoko, H., & Amrullah, A. (2023). Analisis Efek Augmentasi Dataset dan Fine Tune pada Algoritma Pre-Trained Convolutional Neural Network (CNN). *Jurnal Teknologi Informasi dan Ilmu Komputer*, *10*(4), 763–768. https://doi.org/10.25126/jtiik.20241046583

Sesar Husen Santosa, Heryudianto Vibowo, Agung Prayudha Hidayat, Ridwan Siskandar, Khoirul Aziz Husyairi, Bayu Suriaatmaja Suwanda, & Annisa Rizkiriani. (2024a). Pelatihan Cara Penyajian Makanan yang Baik dalam Upaya Peningkatan Kinerja Pemasaran Produk UMKM Warung Nasi Kota Bogor. *JURPIKAT: Jurnal Pengabdian Kepada Masyarakat*, *5*(2), 332–342. https://doi.org/10.37339/jurpikat.v5i2.1498

Sesar Husen Santosa, Heryudianto Vibowo, Agung Prayudha Hidayat, Ridwan Siskandar, Khoirul Aziz Husyairi, Bayu Suriaatmaja Suwanda, & Annisa Rizkiriani. (2024b). Pelatihan Cara Penyajian Makanan yang Baik dalam Upaya Peningkatan Kinerja Pemasaran Produk UMKM Warung Nasi Kota Bogor. *JURPIKAT: Jurnal Pengabdian Kepada Masyarakat*, *5*(2), 332–342. https://doi.org/10.37339/jurpikat.v5i2.1498

Shafa, R. A., & Andono, P. N. (2025). Pendeteksi Visual Makanan dan Jumlah Kalorinya Menggunakan Algoritma Mask R-Cnn Berbasis Bot Telegram. *JIPI: Jurnal Ilmiah Penelitian dan Pembelajaran Informatika*, *10*(1), 641–651. https://doi.org/10.29100/jipi.v10i1.6972

Shen, C., Wang, R., Nawazish, H., Wang, B., Cai, K., & Xu, B. (2024). Machine vision combined with deep learning–based approaches for food authentication: An integrative review and new insights. *Comprehensive Reviews in Food Science and Food Safety*, *23*(6), e70054. https://doi.org/10.1111/1541-4337.70054

Shen, Z., Shehzad, A., Chen, S., Sun, H., & Liu, J. (2020). Machine Learning Based Approach on Food Recognition and Nutrition Estimation. *Procedia Computer Science*, *174*, 448–453. https://doi.org/10.1016/j.procs.2020.06.113

Siskandar, R., Fadhil, M. A., Kusumah, B. R., Irmansyah, I., & Irzaman, I. (2020). Internet of Things: Automatic Plant Watering System Using Android. *Jurnal Teknik Pertanian Lampung (Journal of Agricultural Engineering)*, *9*(4), 297. https://doi.org/10.23960/jtep-l.v9i4.297-310

Siskandar, R., Mandang, T., Hermawan, W., & Irzaman, I. (2023). Engineering of Information Monitoring System Sensor Reading Data Based on Smart Wireless using NVDIA Jetson Nano and Arduino Mega on Agricultural Spraying Machines. *Jurnal Teknik Pertanian Lampung (Journal of Agricultural Engineering)*, *12*(4), 921. https://doi.org/10.23960/jtep-l.v12i4.921-936

Siskandar, R., Santosa, S. H., Hidayat, A. P., Suwanda, B. S., Vibowo, H., Barokah, W. T., Habiburrahman, M., Faqihhudin, M. R., & Nerol, I. D. (2025). Pelatihan Pengembangan Alat Komunikasi Cerdas Keamanan Lingkungan Berbasis Smartphone di Karang Taruna Desa Pakapasan Girang, Kabupaten Kuningan, Jawa Barat. *Jurnal Pengabdian Masyarakat Bhinneka*, *3*(4), 774–784. https://doi.org/10.58266/jpmb.v3i4.259

Siskandar, R., Santosa, S. H., Wiyoto, W., Kusumah, B. R., & Hidayat, A. P. (2022a). Control and Automation: Insmoaf (Integrated Smart Modern Agriculture and Fisheries) on The Greenhouse Model. *Jurnal Ilmu Pertanian Indonesia*, *27*(1). https://doi.org/10.18343/jipi.27.1.141

Siskandar, R., Santosa, S. H., Wiyoto, W., Kusumah, B. R., & Hidayat, A. P. (2022b). Control and Automation: Insmoaf (Integrated Smart Modern Agriculture and Fisheries) on The Greenhouse Model. *Jurnal Ilmu Pertanian Indonesia*, *27*(1). https://doi.org/10.18343/jipi.27.1.141

Siskandar, R., Wiyoto, W., Hendriana, A., Ekasari, J., Kusumah, B. R., Halim, G., & Nugraha, I. J. (2022). Automated Redox Monitoring System (ARMS): An Instrument for Measuring Dissolved Oxygen Levels Using a Potential Redox Sensor (ORP) in a Prototype of Shrimp Farming Pond with an Internet-Based Monitoring System. *Journal of Aquaculture and Fish Health*, *11*(2), 238–246. https://doi.org/10.20473/jafh.v11i2.31487

Solihin, A., Mulyana, D. I., & Yel, M. B. (2022). Klasifikasi Alat Musik Tradisional Papua menggunakan Metode Transfer Learning Dan Data Augmentasi. *5*.

Sonita, A. (2018). Aplikasi Pendeteksi Obat dan Makanan Menggunakan OCR. *Jurnal Informatika UPGRIS*, *4*(1), 2447–6645.

Sutarti & Fariza Syaqialloh. (2025). Klasifikasi dan Pengenalan Emosi dari Ekspresi Wajah Menggunakan CNN-BiLSTM dengan Teknik Data Augmentation. *Decode: Jurnal Pendidikan Teknologi Informasi*, *5*(1), 79–91. https://doi.org/10.51454/decode.v5i1.1038

Talaat, F. M., El-Sappagh, S., Alnowaiser, K., & Hassan, E. (2024). Improved prostate cancer diagnosis using a modified ResNet50-based deep learning architecture. *BMC Medical Informatics and Decision Making*, *24*(1), 23. https://doi.org/10.1186/s12911-024-02419-0

Targ, S., Almeida, D., & Lyman, K. (2016). *Resnet in Resnet: Generalizing Residual Architectures* (arXiv:1603.08029). arXiv. https://doi.org/10.48550/arXiv.1603.08029

Theckedath, D., & Sedamkar, R. R. (2020a). Detecting Affect States Using VGG16, ResNet50 and SE-ResNet50 Networks. *SN Computer Science*, *1*(2), 79. https://doi.org/10.1007/s42979-020-0114-9

Theckedath, D., & Sedamkar, R. R. (2020b). Detecting Affect States Using VGG16, ResNet50 and SE-ResNet50 Networks. *SN Computer Science*, *1*(2), 79. https://doi.org/10.1007/s42979-020-0114-9

Theodore Armand, T. P., Nfor, K. A., Kim, J.-I., & Kim, H.-C. (2024). Applications of Artificial Intelligence, Machine Learning, and Deep Learning in Nutrition: A Systematic Review. *Nutrients*, *16*(7), 1073. https://doi.org/10.3390/nu16071073

Tian, X., & Chen, C. (2019). Modulation Pattern Recognition Based on Resnet50 Neural Network. *2019 IEEE 2nd International Conference on Information Communication and Signal Processing (ICICSP)*, 34–38. https://doi.org/10.1109/ICICSP48821.2019.8958555

Triloka, J., & Mutiara, S. (2025). Evaluasi Kinerja Model Deep Learning dalam Memprediksi Kejadian Hujan Di Wilayah Panjang Bandar Lampung. *Jurnal Informatika*, *25*(1). https://doi.org/10.30873

Udayana, I. P. A. E. D., & Nugraha, P. G. S. C. (2020). Prediksi Citra Makanan Menggunakan Convolutional Neural Network Untuk Menentukan Besaran Kalori Makanan. *Jurnal Teknologi Informasi dan Komputer*, *6*(1), 30–38. https://doi.org/10.36002/jutik.v6i1.1001

Vianda, R. I. Y., Anjarwati, P., Pratama, H. A., Akbar, R. M., & Irawan, R. D. (2025). Klasifikasi Citra Bunga Multikelas Menggunakan Convolutional Neural Network (CNN). *Seminar Nasional Teknologi Informasi dan Bisnis*.

Wahyudiningsih, N. T., Fardani, C. S. S., Pangesti, R. A. N., Halim, G., Nugraha, I. J., Firdaus, M. A. A., Roihan, M., Mujib, M. L. H., Kusumah, B. R., & Siskandar, R. (2022). Rekayasa Sistem Deteksi Dini Corona Virus Disease Sebagai Solusi Pencegahan Penyebaran Virus.

Wan, J., Li, B., Wang, K., Teng, X., Wang, T., & Mao, B. (2024). An Improved ResNet50 for Environment Image Classification. *Procedia Computer Science*, *242*, 1000–1007. https://doi.org/10.1016/j.procs.2024.08.246

Wasilah, Q. S. A., Dikananda, A. R., & Rohman, D. (2025a). Implementasi Cnn Resnet50 Untuk Mendeteksi Kualitas Buah Dan Sayuran Di Pasar Tradisional. *9*(3).

Wasilah, Q. S. A., Dikananda, A. R., & Rohman, D. (2025b). Implementasi Cnn Resnet50 Untuk Mendeteksi Kualitas Buah Dan Sayuran Di Pasar Tradisional. *3 Juni 2025*, *9*(3).

Wen, L., Li, X., & Gao, L. (2020). A transfer convolutional neural network for fault diagnosis based on ResNet-50. *Neural Computing and Applications*, *32*(10), 6111–6124. https://doi.org/10.1007/s00521-019-04097-w

Wiyoto, W., Hendriana, A., Siskandar, R., Mashita, N., Mahendra, T., Cahyo, A. D., Arzi, J. R. A., Aulia, S. S., & Ekasari, J. (2022). Analysis of water and sediment quality in Pacific white leg shrimp Litopenaeus vannamei culture with different sediment redox potential. *Jurnal Akuakultur Indonesia*, *21*(1), 59–67. https://doi.org/10.19027/jai.21.1.59-67

Wu, Z., Shen, C., & Van Den Hengel, A. (2019). Wider or Deeper: Revisiting the ResNet Model for Visual Recognition. *Pattern Recognition*, *90*, 119–133. https://doi.org/10.1016/j.patcog.2019.01.006

Yoridho, D. D., Adi, S. H., & Siskandar, R. (2020). Rancang Bangun Sistem Navigasi Kekeringan dan Meluapnya Air pada Lahan Berbasis web di Balitklimat (Bag. 144-151). *Indonesian Journal of Science*, *1*(3).

You, H., Zhou, M., Zhang, J., Peng, W., & Sun, C. (2023). Sugarcane nitrogen nutrition estimation with digital images and machine learning methods. *Scientific Reports*, *13*(1), 14939. https://doi.org/10.1038/s41598-023-42190-2

Yunus, R., Arif, O., Afzal, H., Amjad, M. F., Abbas, H., Bokhari, H. N., Haider, S. T., Zafar, N., & Nawaz, R. (2019). A Framework to Estimate the Nutritional Value of Food in Real Time Using Deep Learning Techniques. *IEEE Access*, *7*, 2643–2652. https://doi.org/10.1109/ACCESS.2018.2879117

Zidni, E., & Akbar, M. (2024). Klasifikasi Citra Makanan Khas Kota Pasuruan menggunakan Convolutional Neural Network. *1*(2).