E-ISSN: 2962-6110
P-ISSN: 2964-7843
JSRET
jsret.knpub.com
Journal of Scientific Research, Education, and Technology

Applying Convolutional Neural Networks for Real-Time Recognition of Indonesian Traditional Foods

Ananta Rizqi Adiyasa, Ledy Elsera Astrianty
Universitas Teknologi Yogyakarta

ABSTRACT

This study aims to develop an image-based recognition system for Indonesian traditional foods to support the preservation of Nusantara culinary heritage in the digital era using the Convolutional Neural Network (CNN) method. This research was conducted due to the very limited number of studies specifically focused on classifying Indonesian regional traditional foods. Using a transfer learning approach, the pre-trained ResNet50 model was employed as the main architecture, with fine-tuning applied to the final layers to adapt the classification to 13 categories of Indonesian traditional foods. The dataset consisted of 1,560 images that underwent preprocessing and data augmentation to enhance the model's generalization performance. Evaluation results show that the model achieved an accuracy of 81%, with precision, recall, and F1-score values indicating strong classification performance across most classes. The model was integrated into a user interface system to support real-time image prediction. System testing demonstrated fast response capabilities and high prediction confidence. Overall, this study confirms that CNNs with transfer learning can serve as an effective solution for recognizing Indonesian traditional foods and hold potential for further development as an educational medium and a tool for promoting local culinary culture.

Keywords: *Image Recognition,Deep Learning, CNN, Transfer Learning, Traditional Food*

Corresponding author
Name: Ananta Rizqi Adiyasa
Email: rizqiannt@gmail.com

INTRODUCTION

Food recognition has gained increasing attention in the field of multimedia (Min et al., 2020). Indonesia is well known for its cultural diversity, including its culinary heritage, which reflects regional identity and local wisdom. Each province in Indonesia owns unique traditional foods that serve as cultural markers and attractions for culinary tourism. Food is one of the most fundamental and common ways to distinguish individuals from other people or cultures. (Riyadi, Putro, & Parantika, 2023). However, in the midst of rapid globalization and digitalization, the preservation of traditional culinary heritage is facing serious challenges. Younger generations tend to prefer fast food that is more widely promoted in digital media. Various foods that are unique, visually appealing, and delicious have contributed to the increasing diversity of culinary variations (Thiodorus, Prasetia, Ardhani, & Yudistira, 2021). This condition leads to many regional delicacies becoming less recognized and potentially forgotten.

One potential approach to support culinary preservation and promotion is the development of digital image-based food classification systems using Artificial Intelligence (AI) technology. An automated system capable of identifying food in images can help educate younger generations and promote the rich diversity of Indonesian culinary heritage (Kusumo & Aditya, 2024). This technology enables computers to automatically recognize visual objects such as food based on image features. In the context of regional food recognition, computer vision–based image processing systems play an important role as educational media and promotional tools for Indonesian culinary culture in the digital era.Food image recognition is a promising application of visual object recognition in the field of computer vision (Lu, 2016).

The method used in this study is Convolutional Neural Network (CNN), a deep learning architecture specifically designed for image recognition. CNN is one of the most widely used and significants methods in visual recognition, Its because CNNs are designed to mimic the visual recognition system of the human visual cortex, enabling them to effectively process image information. (Peryanto, Yudhana, & Umar, 2019) This demonstrates the potential of CNN to learn the visual characteristics of food, making it suitable for identifying traditional cuisine. According to (Darojat, Sari, & Wihandika, 2021) CNN has advantages in recognizing Indonesian traditional foods due to its ability to learn visual patterns related to texture, color, and shape. Moreover, CNN has proven to outperform SVM in food recognition tasks (Udayana & Nugraha, 2020). These factors reinforce the application of CNN as a technological effort to preserve traditional culinary heritage through accurate and adaptive visual recognition.

However, training CNN from scratch requires a large dataset and computational time. To address this challenge, transfer learning offers an alternative through the use of pre-trained models such as ResNet50. Transfer learning is a technique that leverages knowledge from previously trained models on related tasks to accelerate learning in new tasks (Hosna et al., 2022). By using transfer learning, the features learned from a large dataset can be transferred to a model trained on a smaller dataset (Faturrahman et al., 2023)

Since specific research on classifying Indonesian traditional foods is still very limited, this study aims to (1)Develop a CNN-based image classification model using ResNet50. (2)It is also the first study to develop a user interface that implements the model in a real-time system for food identification as part of cultural promotion efforts.

METHOD

This study employs a quantitative experimental approach by implementing a Convolutional Neural Network (CNN) model to classify images of Indonesian regional traditional foods. In general, the research consists of seven main stages.

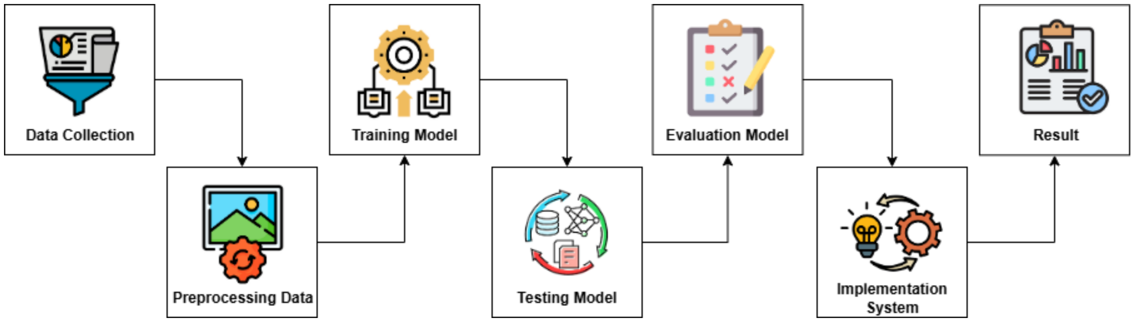

Figure 1 Method

1. Data Collection

The data used in this study consist of images of traditional foods from various regions in Indonesia. The dataset was manually collected from various relevant sources such as culinary websites, image provider platforms, and public datasets. The collection process was carried out by considering image quality and the representation of each region. The dataset used consists of 1,560 images divided into 13 categories of regional foods. Each category contains 120 images with variations in lighting and shooting angles to increase data diversity. Attributes such as color, texture, and shape, which are not always consistent, also make automatic image-based food recognition a highly challenging task (Kiourt, Pavlidis, & Markantonatou, 2020). The food data used in this study are as follows:

Table 1 Food Class

No.	Food	No.	Food
1.	Ayam Betutu	8.	Kerak Telor
2.	Ayam Taliwang	9.	Papeda
3.	Bika Ambon	10.	Pempek
4.	Coto	11.	Rawon
5.	Empal Gentong	12.	Rendang
6.	Gudeg	13.	Telor Asin
7.	Gulai Belacan		

2. Preprocessing

The collected image data then underwent a preprocessing stage to prepare the data so that it aligns with the input format required by the CNN model. In this stage, each image was resized to 224 × 224 pixels, pixel value normalization was performed, and data augmentation The purpose of this process is to improve model generalization (while at the same time ensuring that the class labels of the data do not change) (Irawan, 2024). as well as to increase the variation of the training data and prevent overfitting. This study employed several data augmentation techniques with parameters set to 0.2, indicating that transformations were applied within a 20% range of the original image characteristics. This value was chosen to increase data variability while ensuring that the augmented images did not deviate too far from the original visual patterns and characteristics.

Table 2 Augmentation Techniques

Augmentation	Parameters
Zoom	0.2
Flip	Horizontal & Vertical
Rotation	0.2
Translation	0.2
Contrast	0.2
Brightness	0.2

3. Training Model

The training stage was conducted using TensorFlow, a framework for building and implementing machine learning and deep learning models. (Mahaputri, Gede, & Wisana, 2022). Fine-tuning was performed on the final layers to adjust the number of classes according to the categories of Indonesian traditional foods. The dataset was divided into 80% training data and 20% testing data. The model was trained using the Adam optimizer with a batch size of 32, a learning rate of 0.0001, and a total of 25 epochs. The model also utilized several important parameters, including L2 regularization on dense layers, dropout to prevent overfitting, and class weights to handle data imbalance.

In the initial experiment, the researchers tested MobileNetV2, but its performance was less optimal for the characteristics of the available data. Therefore, ResNet50 was selected as a more suitable architecture to achieve better accuracy.

4. Testing Model

After the training process was completed, the model was tested using test data that had never been involved in the training process. The objective was to evaluate the model's ability to recognize new images and assess its level of generalization. The testing was conducted by calculating evaluation metrics such as accuracy, precision, recall, and F1-score. The F1-score was used to measure multiclass performance by taking the weighted average of the F1-score across all classes (Mahaputri, Kristian, & Setyati, 2022).

5. Evaluation Model

The evaluation was carried out using a confusion matrix as a parameter for analyzing the model's performance. The confusion matrix illustrates the relationship between predictions and actual labels, allowing the number of correct and incorrect classifications for each class to be identified. The accuracy value in classification represents the percentage of data records that are correctly classified (Wulandari et al., 2020). In addition, overall accuracy, precision, and recall were calculated to provide a quantitative overview of the model's effectiveness in recognizing Indonesian regional traditional foods.

6. Implementation System

Once the model had been developed through a series of training and evaluation processes to achieve its optimal configuration and performance, the next stage was to implement the model into a user interface (UI). This implementation aimed to provide a system that is easy to use and accessible to users interactively. At this stage, the trained model was integrated into a website so that the system could accept food image inputs, process them in real time, and generate predictions.

The user interface was built using the Flask framework, which enabled the deployment of the trained model on a lightweight and flexible web application, allowing users to input the form of food images, process them in real time, and generate predictions.

7. Final Result

The final outcome of this study is an Indonesian traditional food detection system capable of identifying the food category in images uploaded by users. The system displays prediction results that include the name of the food, its region of origin, and the confidence score generated by the model for that prediction.

FINDING AND DISCUSSION

Evaluation Model

After configuring several parameters, the best model in this study was built using the ResNet50 architecture based on transfer learning with pre-trained weights from ImageNet. The base layers of ResNet50 were frozen in the initial stage to preserve their general feature extraction capabilities, and fine-tuning was then performed on the final layers to adapt the model to the visual characteristics of the 13 classes of Indonesian traditional foods.

Based on the evaluation results, the model achieved an accuracy of 81% and demonstrated strong classification performance. Thus, the resulting model configuration is considered optimal and ready to be implemented in a real-time Indonesian regional food classification system.

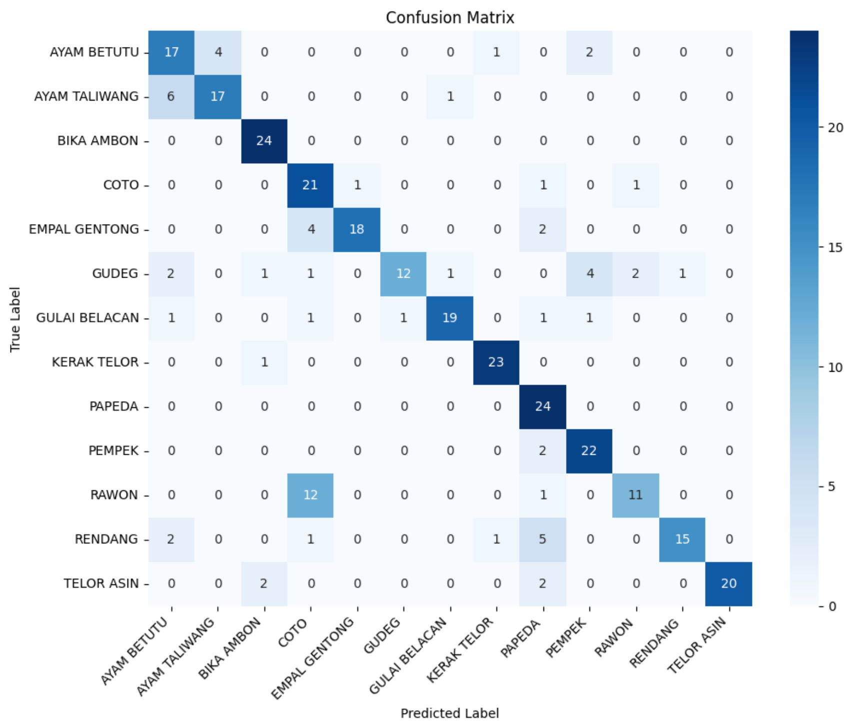

Figure 2 Confussion Matrix of the ResNet50 Model

The confusion matrix from the training and validation results was used to measure how accurately the model can recognize each class. Specifically, the model showed relatively high predictive accuracy (robust performance) for several classes, such as Bika Ambon, Papeda, and Kerak Telor. This indicates that the model successfully learned the visual features of these categories very well.

However, there were significant pattern differences in several other classes, particularly Rendang and Rawon. These misclassifications indicate the presence of feature overlap between these classes in the training dataset, which limits the model's ability to generalize and distinguish them accurately.

Therefore, further model improvements should focus on enhancing the quality and quantity of training data for the underperforming classes, as well as exploring feature engineering techniques or adjusting the model architecture to improve the discriminatory power between visually similar classes.

Table 3 Classification Report

	Precision	**Recall**	**F1-score**
Ayam Betutu	0.61	0.71	0.65
Ayam Taliwang	0.72	0.95	0.82
Bika Ambon	0.95	1.00	0.98
Coto	0.68	0.80	0.74

Empal Gentong	0.95	0.75	0.84
Gudeg	0.91	0.80	0.85
Gulai Belacan	0.90	0.79	0.84
Kerak Telor	0.92	0.96	0.94
Papeda	0.63	1.00	0.77
Pempek	0.76	0.92	0.83
Rawon	0.87	0.50	0.63
Rendang	0.94	0.62	0.75
Telor Asin	1.00	1.00	1.00
Accuracy			0.81
Macro avg	0.83	0.83	0.81
Weighted avg	0.83	0.82	0.81

The evaluation results show that the developed CNN model is capable of classifying Indonesian traditional foods with an overall accuracy of 0.81. On average, the model's performance is also reflected in the macro average precision of 0.83, recall of 0.83, and F1-score of 0.81, indicating that the model possesses good generalization capability across all classes. Based on the per-class metrics, the model demonstrates very high predictive performance in the Bika Ambon, Telor Asin, and Kerak Telor classes, with precision, recall, and F1-score values that are nearly perfect. This confirms that the visual features of these foods were effectively learned by the model.

However, several classes such as Ayam Betutu, Rawon, and Rendang exhibit lower recall values. This indicates that the model still has difficulty consistently recognizing all samples in these classes. The cause of this issue may stem from similarities in texture and color among certain classes that share similar visual characteristics, thereby increasing the likelihood of misclassification.

Overall, the obtained metrics confirm that the CNN model has achieved a fairly competitive performance in the task of recognizing Indonesian traditional foods, although there remains room for improvement in classes that show an imbalance between precision and recall. Enhancement efforts such as increasing data variation, optimizing the model architecture, and applying more class-specific augmentation techniques are needed to achieve more balanced classification performance.

Final Result

The best CNN model obtained from the training and evaluation process was then integrated into a user interface system to support real-time food image prediction. This implementation aimed to ensure that the model not only performed theoretically within a testing environment but was also capable of being applied in real-world usage scenarios. Testing was conducted by providing food image inputs directly through the camera or the image upload feature in the application. The results showed that the system was able to deliver prediction responses quickly and accurately.

The displayed information includes the detected food name as well as the confidence score, which serves as an indicator of the model's certainty regarding the generated prediction. Overall, the synchronization between the model and the system components functioned smoothly, enabling the food detection feature to operate stably and meet user needs. These findings confirm that the developed solution successfully achieved the objectives of the study, namely presenting an artificial intelligence based Indonesian traditional food recognition system that is effective, easily accessible, and capable of producing predictions with a high level of confidence.

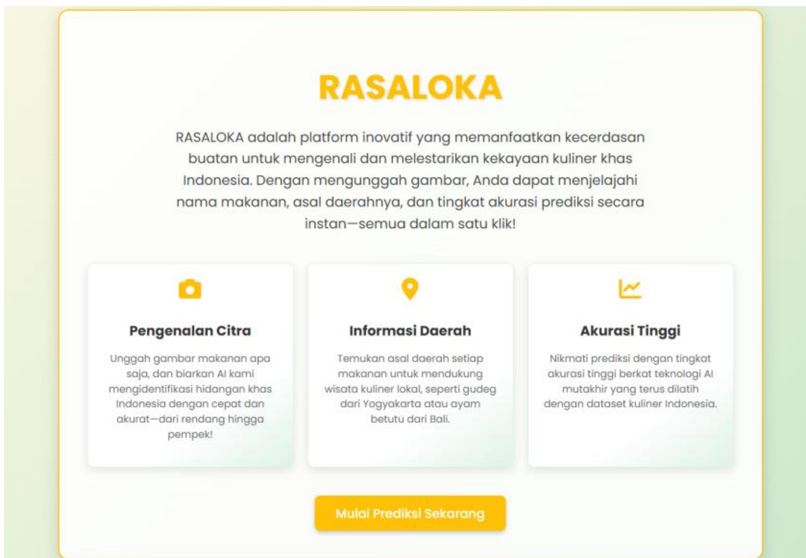

Figure 3 Home Page

Figure 3 shows the main interface of the website. The feature page provides an overview of the purpose and capabilities of RASALOKA. The system is described as an artificial intelligence–based platform designed to recognize and preserve the richness of Indonesia's traditional culinary heritage. It includes features such as image recognition, regional information, and high prediction accuracy. At the bottom of the page, there is a 'Start Prediction Now' button that directs users to the Prediction page.

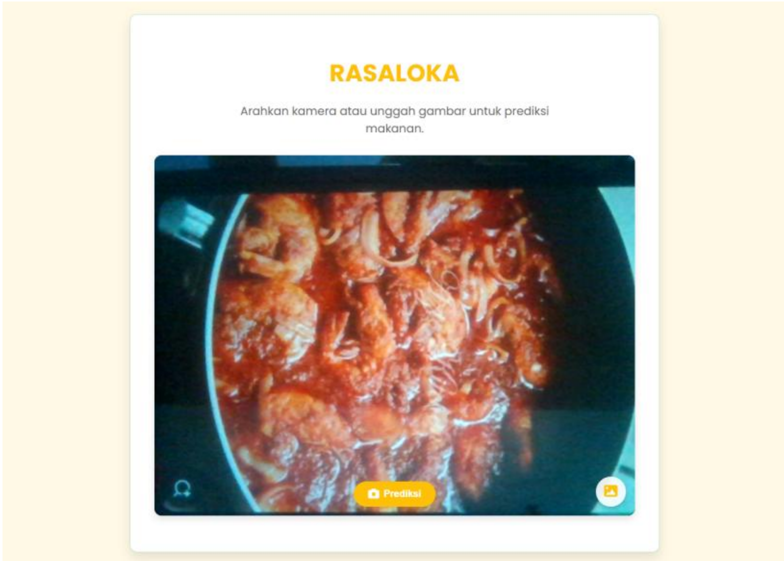

Figure 4 Prediction Page

Figure 4 shows the display of the prediction page. Users can capture a frame directly or select an image from their directory using the gallery icon located at the bottom.

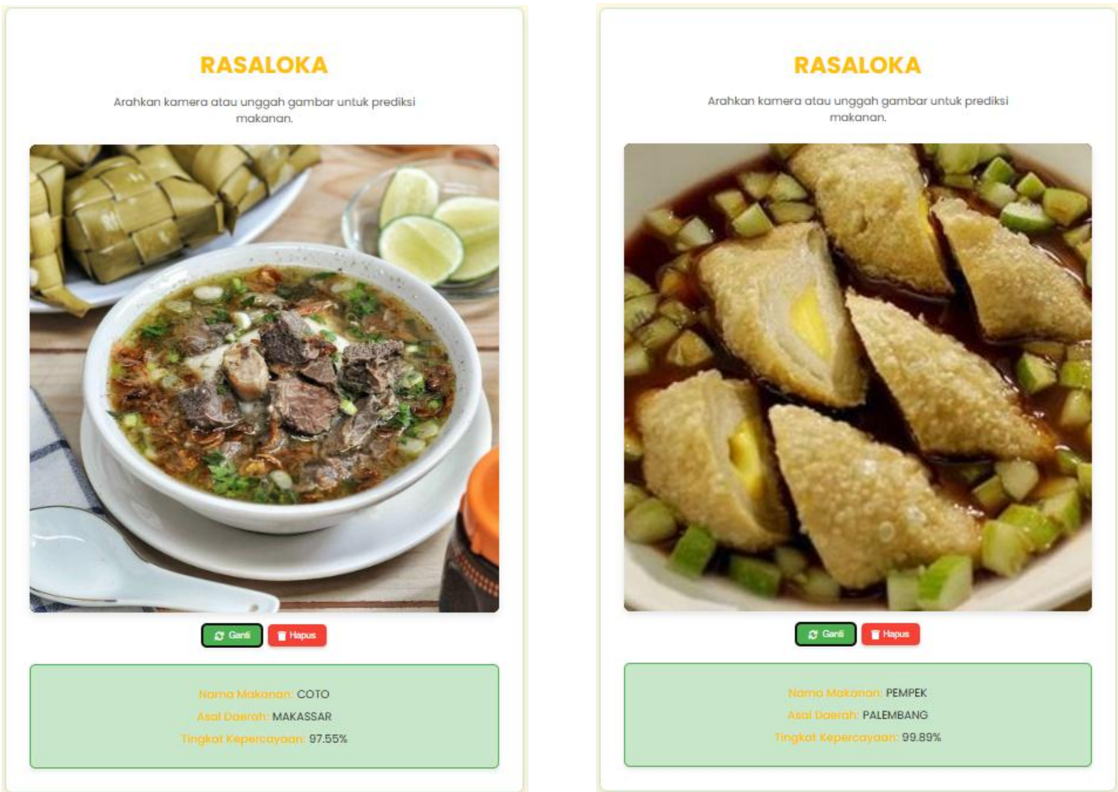

Figure 5 Result Page

The final display after a successful prediction. The model was able to predict the image accurately and demonstrated a very high confidence level, reaching 99.89%.

DISCUSSION

The results of this study show that the Convolutional Neural Network model based on transfer learning using the pre-trained ResNet50 architecture is capable of classifying images of Indonesian traditional foods with a relatively high accuracy of 81%. This finding indicates that the model has effectively learned the visual patterns and characteristics of the foods such as color, texture, and shape resulting in strong performance across most classes.

Compared to previous studies, the results of this research demonstrate consistent evidence that CNN's remain effective for detecting traditional foods despite having limited datasets. The study by (Kusumo & Aditya, 2024) achieved an F1-score of only about 65%, while (Darojat et al., 2021) reported around 60%. In contrast, this study reached an F1-score of 81%, indicating a significant improvement enabled by the use of transfer learning with the ResNet50 architecture. This effectiveness aligns with findings by (Hosna et al., 2022), who stated that pre-trained models can enhance performance on domain-specific datasets while requiring more efficient training. Thus, this study further strengthens the literature suggesting that transfer learning is an ideal solution for classifying regional foods, which typically lack large and standardized datasets.

Additionally, this research successfully developed an interactive user interface (UI) that allows users to utilize the system directly. This is a key advantage, as most prior studies did not integrate their models into a functional UI and were generally limited to laboratory-level testing.

Despite the positive results, several limitations should be considered. One major issue is misclassification among classes with highly similar visual characteristics. For example, foods such as Rendang, Rawon, and Ayam Betutu are often misclassified due to their dark textures, brownish-black coloration, and similar thick-sauce presentation. Limited variation in lighting, camera angles, and serving styles further contributes to the model's difficulty in distinguishing the visual features unique to each dish. This error analysis demonstrates that the model requires a more diverse dataset to better identify fine-grained visual distinctions. Increasing the dataset with variations in lighting conditions, camera perspectives, and presentation styles has strong potential to reduce misclassification rates among visually similar food classes.

CONCLUSION

This study demonstrates that utilizing a Convolutional Neural Network (CNN) with a transfer learning approach based on the ResNet50 architecture is effective for classifying Indonesian traditional foods, achieving an accuracy of 81%. This result indicates that the model successfully learned key visual patterns such as color, texture, and shape, leading to strong predictive performance across most food classes. In addition, the model was successfully integrated into a real-time system, allowing users to obtain predictions quickly and informatively.

These findings carry important implications for the digitalization and cultural promotion of Indonesian cuisine. The implementation of a system capable of recognizing traditional foods along with their regional information has strong potential for use in educational platforms, tourism promotion, and cultural preservation initiatives. The integration of image recognition technology in the context of traditional culinary heritage demonstrates that artificial intelligence can serve as a modern tool to preserve and promote Indonesia's diverse culinary culture to a broader audience.

For future research, improving the quality and diversity of the dataset is highly recommended, especially to reduce misclassification among foods with similar visual characteristics. Further development of mobile-based implementations is also suggested to enhance usability in practical, real-world scenarios. Evaluating lighter CNN architectures such as MobileNet or EfficientNet is recommended to optimize performance on devices with limited computational resources. Overall, this study provides an AI-driven framework for recognizing Indonesian traditional foods, combining cultural preservation with real-time technological applications.

REFERENCES

Darojat, M. D., Sari, Y. A., & Wihandika, R. C. (2021). Convolutional Neural Network untuk Klasifikasi Citra Makanan Khas Indonesia. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *5*(11), 4764–4769. http://j-ptiik.ub.ac.id

Faturrahman, R., Hariyani, Y. S., & Hadiyoso, S. (2023). Klasifikasi Jajanan Tradisional Indonesia berbasis Deep Learning dan Metode Transfer Learning. *ELKOMIKA: Jurnal Teknik Energi Elektrik, Teknik Telekomunikasi, & Teknik Elektronika*, *11*(4), 945. https://doi.org/10.26760/elkomika.v11i4.945

Hosna, A., Merry, E., Gyalmo, J., Alom, Z., Aung, Z., & Azim, M. A. (2022). Transfer learning: a friendly introduction. *Journal of Big Data*, *9*(1). https://doi.org/10.1186/s40537-022-00652-w

Irawan, P. N. C. (2024). *Implementasi Deep Learning Menggunakan Algoritma Convolutional Neural Network (CNN) Dalam Klasifikasi Gambar Makanan Untuk Menentukan Kandungan Kalori Pada Makanan*.

Kiourt, C., Pavlidis, G., & Markantonatou, S. (2020). Deep Learning Approaches in Food Recognition. In *Learning and Analytics in Intelligent Systems* (Vol. 18, pp. 83–108). Springer Nature. https://doi.org/10.1007/978-3-030-49724-8_4

Kusumo, W. P., & Aditya, C. S. K. (2024). Klasifikasi Citra Makanan Berdasarkan Asal Daerah Menggunakan Convolutional Neural Network Food Image Classification Based on Regional Origin using Convolutional Neural Network. In *Februari* (Vol. 23, Issue 1).

Lu, Y. (2016). Food Image Recognition by Using Convolutional Neural Networks (CNNs). *Michigan State University,*. http://arxiv.org/abs/1612.00983

Mahaputri, C., Gede, D., & Wisana, H. (2022). Pengenalan Makanan Tradisional Nusantara dengan Menggunakan Metode Convolutional Neural Network (CNN). *Journal of Information System and Computer*, *1*.

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

Min, W., Liu, L., Wang, Z., Luo, Z., Wei, X., Wei, X., & Jiang, S. (2020). ISIA Food-500: A Dataset for Large-Scale Food Recognition via Stacked Global-Local Attention Network. *MM 2020 - Proceedings of the 28th ACM International Conference on Multimedia*, 393–401. https://doi.org/10.1145/3394171.3414031

Peryanto, A., Yudhana, A., & Umar, R. (2019). Rancang Bangun Klasifikasi Citra Dengan Teknologi Deep Learning Berbasis Metode Convolutional Neural Network. *Jurnal Format*, *8*, 2089–5615. https://publikasi.mercubuana.ac.id/index.php/format/article/view/7849/pdf

Riyadi, F. A., Putro, D. A., & Parantika, A. (2023). Identintas Budaya Dan Kuliner Yogyakarta Sebagai Gastronomi Dan Perspektif Pariwisata Yang Berkelanjutan. *Jurnal Ilmiah Wahana Pendidikan*.

Thiodorus, G., Prasetia, A., Ardhani, L. A., & Yudistira, N. (2021). Klasifikasi citra makanan/non makanan menggunakan metode Transfer Learning dengan model Residual Network. *Teknologi : Jurnal Ilmiah Sistem Informasi*, *11*(2), 74–83. https://doi.org/10.26594/teknologi.v11i2.2402

Udayana, I. P. A. E. D., & Nugraha, P. G. S. C. (2020). *Prediksi Citra Makanan Menggunakan Convolutional Neural Network Untuk Menentukan Besaran Kalori Makanan*.

Wulandari, I., Yasin, H., & Widiharih, T. (2020). Klasifikasi Citra Digital Bumbu Dan Rempah Dengan Algoritma Convolutional Neural Network (CNN). *JURNAL GAUSSIAN*, *9*, 273–282. https://ejournal3.undip.ac.id/index.php/gaussian/