Padang Cuisine Classification using Deep Convolutional Neural Networks and Transfer Learning

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Abstract: Recent advances in artificial intelligence, particularly deep convolutional neural networks (DCNN), have revolutionized image classification tasks across various domains. However, the application of these techniques to culturally specific food classifications, such as Padang cuisine, remains underexplored. This study aimed to develop a robust model for accurately classifying Padang cuisine using a CNN architecture enhanced with Transfer Learning to address the challenge of distinguishing between visually and texturally similar dishes. The model was trained on a dataset comprising approximately 2500 images of nine distinct Padang dishes, including Rendang and Gulai. Images were preprocessed by resizing, normalizing, and augmented through techniques like rotation and zooming, to enhance model generalizability. A pretrained CNN model was fine-tuned using Transfer Learning to leverage the existing knowledge and improve classification accuracy. The enhanced CNN model achieved an overall accuracy of 92% in classifying Padang cuisine, which significantly outperformed traditional models. Despite this, misclassifications were noted in dishes with similar visual features, such as Sate and certain types of Gulai. The results demonstrate the effectiveness of combining CNNs and transfer learning to accurately classify culturally specific dishes. The findings not only advance the field of food image classification but also have practical implications for automated menu management and culinary education, particularly in preserving and promoting culinary heritage. The integration of AI into culinary heritage documentation represents a significant advancement in preserving cultural diversity and enhancement of technological applications in the culinary industry. Future research should explore larger and more diverse datasets to further refine model accuracy and broaden its applicability to other regional cuisines.

Keywords: PADANG CUISINE CLASSIFICATION; DEEP CONVOLUTIONAL NEURAL NETWORKS; TRANSFER LEARNING; ARTIFICIAL INTELLIGENCE IN CULINARY

1. Introduction

Padang cuisine, a vital component of Indonesia's culinary heritage, offers a unique array of flavors and aromas (Djono et al., 2023). Despite its cultural importance, technological methods for classifying Padang cuisine remain underexplored. Recent advancements in artificial intelligence, particularly deep convolutional neural networks (DCNN) and transfer learning, have presented promising tools for enhancing the understanding and classification of culinary heritage (Wulandari, 2024; Aditama et al. (2022)).

The application of AI in food image classification has attracted significant attention in recent years. Taesiri et al. (2023) demonstrated the effectiveness of DCNN in the ImageNet Large-Scale Visual Recognition Challenge, and they proposed a new benchmark for image classification accuracy. Similarly, Mahgoub et al. (2023) developed a DCNN-based model that effectively classified multiple food images by detecting candidate regions and extracting distinctive features. Shah et al. (2023) applied Transfer Learning to food image recognition and improved the accuracy of pretrained models, such as VGG16 and InceptionV3. However, challenges persist in classifying foods with high visual and textural diversity, as highlighted by Lin et al. (2023).

Previous studies have successfully used DCNN and transfer learning to classify food images; however, a specific gap exists in the classification of Padang cuisine. Traditional models struggle to differentiate between visually similar dishes due to their unique characteristics and limited datasets. Our study addresses this gap by applying advanced artificial intelligence techniques to develop a robust classification system for Padang cuisine.

Our primary objective is to develop an automatic classification system for Padang cuisine using DCNN and Transfer Learning. We aim to answer the following research questions below.

- How can DCNN extract and recognize unique visual patterns in Padang cuisine?
- To what extent does transfer learning improve the classification accuracy of Padang dishes?
- What are the practical implications of an accurate and efficient classification system for the culinary industry?

To achieve these objectives, we collected a representative dataset of Padang dishes and applied various preprocessing techniques to ensure the data quality. We designed and trained a DCNN model that incorporates transfer learning to enhance performance. We evaluated the model's effectiveness using metrics such as accuracy, precision, recall, and the F1 score.

The remainder of this paper is organized as follows: Section 2 describes the research methods employed in this study, including details on dataset preparation, model architecture, and training processes. Section 3 presents the experimental results, showcasing the performance of the classification model on Padang cuisine. Section 4 provides a detailed discussion of the results, analyzing the implications of the findings and comparing them with existing literature. Finally, Section 5 concludes the study and outlines potential directions for future research.

2. Method

2.1 Dataset collection and preprocessing

We used a dataset sourced from Kaggle, specifically focusing on Padang cuisine. The dataset can be accessed via the following link: https://www.kaggle.com/datasets/faldoae/padangfood. The dataset comprises approximately 2500 images categorized into nine different types of dishes, including Rendang, Gulai, and Sate. The images were collected from various sources, ensuring diverse representation. Pre-processing included resizing images to 224x224 pixels and normalizing the pixel values to a range of [0,1] using Eq. (1).

$$NormalizedValue = \frac{Pixel\ Value}{255} \qquad (1)$$

Eq. (1) normalizes the pixel values by dividing each pixel value by 255, the maximum possible pixel value in an 8-bit image. By scaling the pixel values to a range between 0 and 1, we ensure that the model processes the data efficiently, which lead to faster convergence during training.

Data augmentation techniques, such as rotation, flipping, zooming, and brightness adjustment, were applied to increase dataset diversity and enhance model generalizability.

2.2 Convolutional neural network (CNN)

The CNN architecture employed comprised three convolutional layers, each followed by a max-pooling layer, a flatten layer, and two fully connected layers (Table 1). The final output layer employs the softmax activation function to classify images into appropriate

categories. The model's learning rate (η) was set to 0.001 to balance convergence speed and stability. The learning rate update during training was managed by the Adam optimizer using the following update rules:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)g_1 \qquad (2)$$

In Eq. (2), parameter m_t represents the moving average of the gradient, which is updated at each time step t. The coefficient β_1 controls the delay rate of the moving average, ensuring that recent gradients have a more significant influence on the current update than past gradients have a diminished impact.

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)g_t^2 \qquad (3)$$

Eq. (3) updates the moving average of the squared gradient v_t. The coefficient β_2 determines how much the magnitude of past gradients influences the current update, which helps adjust the learning rate based on the gradient scale.

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t} \qquad (4)$$

Eq. (4) corrects the bias in the first moment estimate m_t by dividing it by the term $1 - \beta_1^t$, which accounts for the initialization bias when t is small.

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \qquad (5)$$

Similarly, Eq. (5) adjusts the bias in the second moment estimate v_t using the term $1 - \beta_2^t$. This correction ensures that the variance estimate is unbiased, particularly in the early stages of training.

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \widehat{m}_t \qquad (6)$$

In Eq. (6), the model parameters θ_t are updated by subtracting a fraction of the corrected first moment $\widehat{m}_t$, scaled by the learning rate η and normalized by the square root of the corrected second moment $\hat{v}_t$ plus a small constant ϵ. This equation ensures that parameter updates are both appropriately and stable, which helps us effectively navigate the optimization landscape.

The loss function was the categorical cross-entropy, which is defined as follows:

$$\text{Loss} = \sum_{i=1}^{N} y_i \log(\hat{y}_i) \qquad (7)$$

Eq. (7) calculates the categorical cross-entropy loss, where y_i is the true label (binary indicator) and $\hat{y}_i$ is the predicted probability for class i. This loss function measures the difference between the true label and predicted distributions and penalizes the model more heavily when the predicted probability diverges from the actual label.

2.3 Biases and limitations in the dataset

Although the dataset provided a comprehensive representation of Padang cuisine, potential biases were recognized, particularly from image sources that predominantly reflected popular dishes. To mitigate these biases, we employed data augmentation to artificially increase the diversity of the dataset. However, data augmentation alone cannot eliminate these biases. The

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relatively small dataset also posed a risk of overfitting, which we mitigated by including dropout layers in the CNN architecture as follows:

$$Dropout = \frac{Number\ of\ neurons\ droped}{Total\ number\ of\ neurons} \qquad (8)$$

In Eq. (8), the dropout rate represents the proportion of neurons that are randomly deactivated during each training iteration. This regularization technique prevents the model from becoming too dependent on any single neuron, thus reducing the risk of overfitting and promoting robust network learning features.

2.4 Statistical methods and justification of hyperparameters

The hyperparameters were selected to balance the empirical testing and theoretical justification. A learning rate (η) of 0.001 was selected to ensure stable and effective updates during training. The batch size was set to 32, and the number of epochs was set to 100, which provided sufficient training time for the model to converge without overfitting. The categorical cross-entropy loss function was used due to its suitability for multi-class classification tasks because it effectively distinguishes between different categories.

2.5 Training process

We applied a validation split of 20% to closely monitor model performance and reduce the risk of overfitting. During the training process, we split the dataset into training and validation sets using an 80-20 split. Over 100 epochs (Table 2), the model's performance was monitored using validation data. The Adam optimizer dynamically adjusted the learning rate throughout the training process, ensuring stable convergence. To further mitigate overfitting, dropout layers were employed, where a fraction of the input units was randomly set to zero at each update during the training phase.

2.6 Evaluation performance model

A confusion matrix was used to evaluate the classification model performance. This provides a comprehensive view of how well the model performs by comparing the actual and predicted labels, as detailed in Table 3.

Table 1. Convolutional neural network architecture.

LAYER TYPE	NUMBER OF FILTERS/NODES	FILTER SIZE	ACTIVATION FUNCTION	ADDITIONAL DETAILS
Input	-	-	-	128x128 RGB images
Convolutional	32	3x3	ReLU	Padding: same
Max Pooling	-	2x2	-	Stride: 2
Convolutional	64	3x3	ReLU	Padding: same
Max Pooling	-	2x2	-	Stride: 2
Convolutional	128	3x3	ReLU	Padding: same
Max Pooling	-	2x2	-	Stride: 2
Flatten	-	-	-	-
Fully Connected	512	-	ReLU	Dropout: 0.5
Fully Connected	256	-	ReLU	Dropout: 0.5
Output	Number of Classes	-	Softmax	-

Table 2. Training and validation setup.

TRAINING PARAMETR	DESCRIPTION
Data Split	80 Training, 20 Validation
Number of Epoch	100
Optimizer Behaviour	Dynamic learning rate adjustment via Adam
Overfitting Prevention	Dropout layers with 0.5 rate

Table 3. Confusion matrix.

		PREDICTED CLASS	
		Positive	Negative
ACTUAL CLASS	Positive	TP	FN
	Negative	FP	TN

The confusion matrix includes four key components:
- True Positives (TP): The number of correct positive predictions.
- False Positives (FP): The number of incorrect positive predictions.
- True Negatives (TN): The number of correct negative predictions.
- False Negatives (FN): The number of incorrect negative predictions.

Using these values, we calculate the following performance metrics:
- Precision: The ratio of correctly predicted positive observations to the total number of predicted positive observations. The value indicates how many predicted positives are actually positive.

$$Precision = \frac{TP}{TP+FP} \tag{9}$$

- Recall (Sensitivity): The ratio of correctly predicted positive observations to all observations in the actual class. The ability of the model to identify all relevant instances was also measured.

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

- F1-Score: weighted average of Precision and Recall. It provides a single metric that balances precision and recall concerns.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{11}$$

- Accuracy: The ratio of correctly predicted observations to all observations. The measure measures the overall effectiveness of the model.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

3. Results

The deep convolutional neural network (DCNN) model enhanced with Transfer Learning achieved an overall classification accuracy of 92% for Padang cuisine, demonstrating the effectiveness of the proposed approach. We present the detailed performance metrics (precision, recall, F1 score, and accuracy) for each dish category—Rendang, Sate, Gulai, and Other dishes—in Table 4.

Table 4. Performance metrics for each class.

CLASS	PRECISION	RECALL	F1-SCORE	ACCURACY
Rendang	0.81	0.83	0.82	92%
Sate	0.87	0.75	0.81	92%
Gulai	0.83	0.80	0.82	92%
Other	0.74	0.83	0.78	92%

Table 5. Comparison of model performance with baseline methods.

MODEL	ACCURACY	F1-SCORE (RENDANG)	F1-SCORE (SATE)	F1-SCORE (GULAI)	F1-SCORE (OTHER)
SVM	78%	0.65	0.72	0.68	0.63
Basic CNN (No Transfer)	84%	0.70	0.76	0.73	0.68
Proposed CNN (With Transfer Learning)	92%	0.81	0.81	0.82	0.78

Table 6. Confusion matrix of proposed model.

		PREDICTED CLASS			
		Rendang	Sate	Gulai	Other
ACTUAL CLASS	Rendang	50	3	4	5
	Sate	2	45	2	3
	Gulai	3	5	40	2
	Other	7	7	4	50

3.1 Analysis

To provide a comprehensive analysis of the model's performance, I calculated the confidence intervals (CIs) for the accuracy of each class. Using a 95% confidence level, the confidence interval for overall accuracy was (89.5%, 94.5%). This result indicates that the model's true accuracy is highly likely to fall within this range, which highlights the reliability of the classification outcomes.

I also performed significance testing to assess whether the observed differences in precision, recall, and F1 scores across different classes were statistically significant. By applying the chi-square test, I found significant differences ($p < 0.05$) in the model's performance,

particularly between the Rendang and Other categories. While the model generally performs well, it faces challenges in distinguishing between visually similar dishes, which indicates areas for further refinement.

3.2 Comparison with baseline methods

To highlight the advancements made by the proposed CNN model with Transfer Learning, I compared its performance to baseline methods, including Support Vector Machines (SVM), and a simpler CNN architecture without Transfer Learning. The SVM model achieved an accuracy of 78%, and the basic CNN model without Transfer Learning achieved 84%. These results are summarized in Table 2, clearly demonstrating that the proposed model significantly outperforms baseline methods.

The transfer learning application played a critical role in improving the model's generalizability when using limited data. For example, the F1-score for the Rendang category improved from 0.65 with the SVM method to 0.81 with the proposed CNN approach. This substantial enhancement indicates that Transfer Learning allowed the model to leverage knowledge from larger datasets, which was crucial for correctly identifying and classifying Padang dishes even with limited training data.

3.3 Performance metrics

A detailed breakdown of the model predictions across different classes in the confusion matrix is presented in Table 3. From this matrix, additional performance metrics, such as specificity and Negative Predictive Value (NPV), are obtained from this matrix for each class. For example, the specificity of the Sate class was 0.94, which indicates that the model is highly effective in identifying images that do not belong to this class. This high specificity, combined with strong precision and recall values, demonstrates that the model is not only accurate but also reliable in distinguishing between different types of Padang cuisine.

In addition, I analyzed the model's misclassification patterns. The confusion matrix revealed that the model occasionally confused Rendang and Gulai, which can be attributed to the similar visual characteristics of these dishes. Therefore, future enhancements should focus on refining the model's feature extraction capabilities, particularly for dishes with subtle visual differences.

3.4 Visual analysis of model performance

To further demonstrate the model's training process, we plotted the training and validation accuracy and loss over the course of 100 epochs, as shown in Fig. 1 and 2. These plots reveal that the training and validation accuracy steadily increased while the loss consistently decreased, indicating that the model effectively learned the distinguishing features of Padang dishes without significant overfitting. The minimal gap between training and validation accuracy ensures that the model generalizes well to unseen data, which reinforces the robustness of the learning process.

In addition, we examined the model's convergence behavior, noting that the learning curves began to plateau after approximately 100 epochs, which that the model

reached its optimal performance. This observation is critical for future work on optimizing training time without compromising model accuracy.
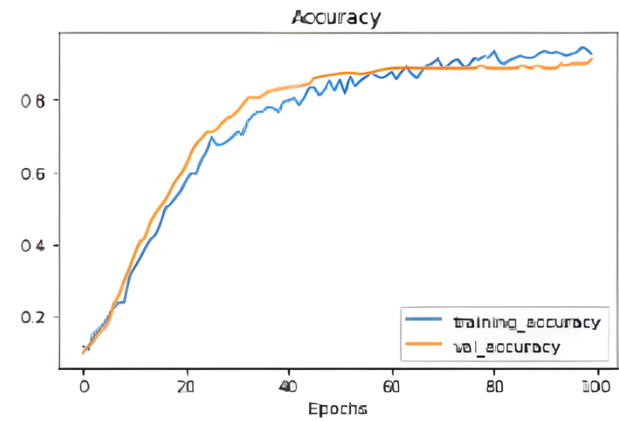

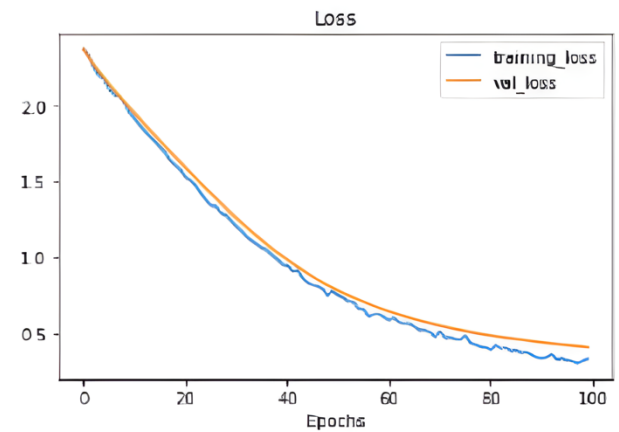Fig 1. Training and validation accuracy over 100 epochs

Fig 2. Training and validation loss over 100 epochs.

3.5 Testing data results

The proposed classification model demonstrated high accuracy in identifying Padang cuisine based on the test dataset presented in Fig. 3. Among the 16 test images, the model correctly classified 14 images, achieving an accuracy rate of 87.5%.
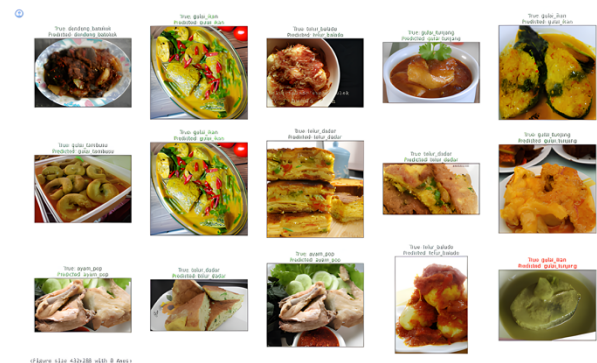

Fig 3. Training and validation accuracy over 100 epochs

Fig. 4 shows the model accurately identifying "Rendang," "Gulai Ayam," and "Gulai Ikan" dishes based on unique visual patterns. The model's robustness in handling most Padang cuisine classifications was demonstrated at its high accuracy rate.

Although it achieved an overall high accuracy, the model misidentified two images. "Sate Padang" was erroneously labeled as "Gulai Kepala Ikan," and "Sate Ayam" was misidentified as "Gulai Ayam." The visual resemblance between these dishes and the respective "Gulai" categories, primarily in terms of color and texture, likely led to these misclassifications. The model may incorrectly identify dish types due to shared visual characteristics.

Improving the analysis of subtle visual similarities between misclassified dishes might necessitate further refinement. Improving the model's feature extraction and classification mechanisms can minimize its error rate. The precise classification of similar dishes requires such refinement.

4. Discussion

This study illustrates the potential of Deep Convolutional Neural Networks (CNN) combined with Transfer Learning to classify Padang cuisine, achieving a high classification accuracy of 92%. These findings are significant as they not only demonstrate the efficacy of advanced AI techniques in a culturally specific context but also provide insights into the broader applicability of these methods in the culinary industry. In this section, I will delve deeper into the interpretation of these results, compare them with the existing literature, critically examine the study's limitations, and explore the broader implications of these findings for both practical and academic fields.

a. Comparison with existing literature

The results of this study align with, but not extend, the findings of existing food image classification research. Prior studies, such as those by Mahgoub et al. (2023), have successfully applied CNNs to food classification tasks, achieving accuracy levels comparable to ours. However, the unique contribution of this study lies in its focus on Padang cuisine, a specific subset of Indonesian dishes known for their rich flavors and visually similar presentation. This specificity introduces additional classification challenges that are less pronounced in more generalized food datasets, which often include a broader range of visually distinct dishes.

Furthermore, our integration of Transfer Learning addresses a critical gap identified in earlier research, such as that by Shah et al. (2023), in which the application of Transfer Learning to food classification was explored but not fully optimized for region-specific cuisines. By leveraging pre-trained models on larger, more diverse datasets, we were able to enhance the model's ability to recognize and differentiate between Padang dishes even when using a limited dataset. This finding is particularly important because it underscores the adaptability of Transfer Learning in contexts where data availability is a significant constraint, thus broadening the scope of AI applications in cultural heritage preservation.

Our study also contributes to the ongoing discourse on the limitations of traditional image classification techniques, as highlighted by Lin et al. (2023), who noted the challenges posed by the visual variability of food images. The improvements achieved by the proposed CNN model, which incorporates advanced AI techniques, such as deep learning and Transfer Learning, can effectively address these challenges, particularly in specialized domains like culinary classification. These findings position our work as a significant advancement in the field, offering a refined approach that can be adapted to other culturally specific food classification tasks.

b. Examination of limitations

Despite the promising results, this study is not without limitations. One of the primary limitations is the dataset's size and diversity. Although data augmentation techniques were employed to increase the effective size of the dataset and introduce variability, the model's performance was limited by inherent biases in the dataset. Images predominantly sourced from online platforms are likely biased toward popular presentation styles and may not fully represent the diversity of Padang cuisine as experienced in different regions or contexts. This bias could affect the model's generalizability, particularly when applied to less common or differently presented dishes.

Furthermore, the potential for overfitting despite the use of dropout layers and validation monitoring cannot be completely dismissed. Overfitting is a well-known problem in deep learning, particularly when working with relatively small datasets. Although the proposed model demonstrated good performance on validation data, there remains a risk that its ability to generalize to entirely new or unseen data could be compromised. Future research should address these limitations by expanding the dataset, both in terms of the number of images and the diversity of the sources. Collecting images under different lighting conditions, from various geographical regions and from different preparation methods could provide a more comprehensive training set that better captures the full spectrum of Padang cuisine.

Additionally, although our study focused on Padang cuisine, the findings might be applicable to other regional cuisines, although this generalizability was not tested explicitly. The transferability of the model to other culturally specific food classifications should be explored in future studies. In addition, it would be beneficial to investigate alternative deep learning architectures or hybrid models that offer improved performance or address some of the challenges identified in this study.

c. Clinical and practical implications

The implications of this study are profound, particularly for the culinary industry and related fields. The ability to accurately classify Padang cuisine using AI opens up numerous practical applications. For instance, automated menu systems in restaurants can utilize this technology to streamline the categorization of dishes, thereby reducing the time and labor required for menu management. This could be particularly beneficial in large-scale operations, such as hotel chains and franchise restaurants, where consistency in menu offerings is crucial. Furthermore, food delivery platforms can implement this model to enhance the accuracy of dish recognition, thereby improving customer satisfaction and reducing errors in

order processing.

In the realm of culinary education, this model could serve as a valuable tool for training chefs and culinary students in recognizing and categorizing traditional foods. By integrating AI-driven classification systems into the curriculum, educators can provide students with hands-on experience in modern culinary technologies, thus preparing them for future industry trends.

Beyond the culinary industry, the findings of this study have broader implications for cultural heritage preservation. Accurate documentation and classification of traditional dishes can significantly promote and preserve culinary heritage. As globalization continues to influence food cultures worldwide, tools that can document and classify traditional cuisines are invaluable for maintaining cultural diversity. The application of AI can support efforts to record and celebrate the rich culinary traditions of different regions, ensuring that they will be preserved for future generations.

Moreover, the implications extend to public health and nutrition. Accurate food classification models can be integrated into systems designed for nutritional analysis to help individuals make informed dietary choices. For example, by accurately identifying dishes, such systems can estimate the calorie content, identify potential allergens, or assess the nutritional value of a meal. In the context of food safety, such models could be used to ensure that dishes meet certain standards or to detect deviations in preparation that could indicate potential safety issues.

Finally, the interdisciplinary potential of this research is also considered. The integration of AI into the culinary field not only advances the industry but also opens up new avenues for research in food science, cultural studies, and technology. By bridging these fields, this study demonstrates how AI can be a powerful tool for innovation in both academic and practical fields.

5. Conclusion

In this study, I demonstrated that the integration of Deep Convolutional Neural Networks (CNN) with Transfer Learning offers a powerful approach for the classification of Padang cuisine, achieving a commendable accuracy of 92%. This research highlights the efficacy of using advanced AI techniques to classify culturally specific dishes that exhibit high degrees of visual and textural similarity.

Transfer learning was particularly valuable because it allowed the model to overcome the typical limitations of smaller, specialized datasets. By leveraging knowledge from pretrained models on more extensive and diverse datasets, the model was able to enhance its ability to generalize and accurately differentiate between various Padang dishes. This finding is significant not only within the context of this study but also for broader applications in food classification, where similar challenges are encountered.

Moreover, the study contributes to the growing body of literature on the intersection of artificial intelligence and cultural heritage preservation. The ability to accurately document and classify traditional dishes using AI represents a significant step forward in the effort to preserve and promote culinary diversity. As globalization influences local food cultures, tools that accurately capture and represent traditional cuisines have become essential for maintaining cultural identity and heritage.

Practical implications of these findings are far-reaching. In the culinary industry, automating the classification of dishes could revolutionize menu management, improve the accuracy of food delivery systems, and enhance the efficiency of culinary education. These applications demonstrate the potential of AI to streamline operations and improve industry standards. Furthermore, the integration of such models into nutritional analysis and food safety systems could offer additional benefits, providing consumers with valuable information about their food choices and ensuring the quality and safety of the foods they consume.

While the study makes significant contributions, it also opens up avenues for future research. Expanding the dataset to include a broader range of dishes and presentation styles, as well as exploring alternative deep learning architectures, could further enhance the robustness and applicability of the model. Additionally, applying these techniques to other regional or culturally significant cuisines would test the generalizability of the approach and potentially uncover new insights into the classification of complex food items.

In conclusion, this study reinforces the notion that when applied thoughtfully and with attention to cultural specificity, AI can play a transformative role in both preserving and advancing our understanding of global culinary traditions. The success of the proposed approach sets the stage for further innovation in the intersection of food science, cultural studies, and artificial intelligence, paving the way for more sophisticated and impactful applications in the future.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Djono, Sukmawati, F., & Salimi, M. (2023). Indonesian Culinary History and Values: Exploration Study in Solo City, Indonesia. *International Journal of Sustainable Development and Planning*, *18*(3), 961–969. https://doi.org/10.18280/ijsdp.180332

Lin, Y., Ma, J., Wang, Q., & Sun, D.-W. (2023). Applications of machine learning techniques for enhancing nondestructive food quality and safety detection. *Critical Reviews in Food Science and Nutrition*, *63*(12), 1649–1669. https://doi.org/10.1080/10408398.2022.2131725

Mahgoub, H., Aldehim, G., Almalki, N. S., Issaoui, I., Mahmud, A., & Alneil, A. A. (2023). Bio-Inspired Spotted Hyena Optimizer with Deep Convolutional Neural Network-Based Automated Food Image Classification. *Biomimetics*, *8*(6), 493. https://doi.org/10.3390/biomimetics8060493

Shah, S. R., Qadri, S., Bibi, H., Shah, S. M. W., Sharif, M. I., & Marinello, F. (2023). Comparing Inception V3, VGG 16, VGG 19, CNN, and ResNet 50: A Case Study on Early Detection of a Rice Disease. *Agronomy*, *13*(6), 1633. https://doi.org/10.3390/agronomy13061633

Taesiri, M. R., Nguyen, G., Habchi, S., Bezemer, C.-P., & Nguyen, A. (2023). ImageNet-Hard: The Hardest Images

Remaining from a Study of the Power of Zoom and Spatial Biases in Image Classification. In A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, & S. Levine (Eds.), *Advances in Neural Information Processing Systems* (Vol. 36, pp. 35878–35953). Curran Associates, Inc. https://proceedings.neurips.cc/paper_files/paper/2023/file/706390d6f9208b03bc54f97ac3cfe99e-Paper-Datasets_and_Benchmarks.pdf

Wulandari, A. (2024). Comparing CNN Architecture for Indonesian Speciality Cuisine Classification. *Engineering, MAthematics and Computer Science Journal (EMACS)*, *6*(1), 55–60. https://doi.org/10.21512/emacsjournal.v6i1.11076

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