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PADANG FOOD IMAGE CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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Abstract—*The recognition of Padang traditional foods presents a challenge because of their high visual similarity, which makes manual classification difficult. This study aims to develop an automatic image classification model for Padang foods using the Convolutional Neural Network (CNN) algorithm. The dataset consisted of 1350 images across nine classes of Padang dishes including omelet, chili egg, cow tendon curry, stuffed intestine curry, fish curry, dendeng batokok, rendang, ayam pop, and fried chicken. The CNN architecture was trained for twenty epochs and evaluated using accuracy, loss, confusion matrix, and testing with new images. The results show that the model reached a final training accuracy of 70.2 percent and a validation accuracy of 65 percent, while testing with unseen images produced correct predictions with moderate confidence levels. These findings suggest that CNN is effective for classifying Padang traditional foods and can be applied in culinary promotion, digital food catalogs, and technology based ordering platforms.*

Keywords: *convolutional neural network, deep learning, image classification, image recognition, Padang food.*

Abstrak—*Pengenalan makanan tradisional Padang merupakan sebuah tantangan karena memiliki kemiripan visual yang tinggi sehingga sulit untuk diklasifikasikan secara manual. Penelitian ini bertujuan untuk mengembangkan model klasifikasi citra makanan Padang secara otomatis dengan menggunakan algoritma Convolutional Neural Network (CNN). Dataset yang digunakan terdiri dari 1350 citra dengan sembilan kelas hidangan Padang yaitu telur dadar, telur balado, gulai kikil, gulai usus isi, gulai ikan, dendeng batokok, rendang, ayam pop, dan ayam goreng. Arsitektur CNN dilatih selama dua puluh epoch dan dievaluasi menggunakan akurasi, loss, confusion matrix, serta pengujian dengan citra baru. Hasil penelitian menunjukkan bahwa model mencapai akurasi pelatihan akhir sebesar 70,2 persen dan akurasi validasi sebesar 65 persen, sedangkan pengujian dengan citra yang belum pernah digunakan menghasilkan prediksi yang benar dengan tingkat kepercayaan sedang. Temuan ini menunjukkan bahwa CNN efektif untuk mengklasifikasikan makanan tradisional Padang dan dapat diterapkan pada promosi kuliner, katalog makanan digital, serta platform pemesanan berbasis teknologi.*

Kata Kunci*: convolutional neural network, deep learning, klasifikasi citra, pengenalan gambar, makanan Padang.*

INTRODUCTION

Indonesia is known as a country rich in Culture, including the richness of traditional culinary arts spread across various regions(Linarti et al., 2024). One of the most prominent culinary arts and has been widely known internationally is Padang food, which originates from West Sumatra Province. Padang food is characterized by a strong spice flavor, an appetizing visual appearance, and unique serving techniques, such as the "hidang" system that serves various types of side dishes simultaneously. In the current era of globalization and digitalization, automatic food recognition and classification through digital images is becoming increasingly important, both for cultural preservation, tourism promotion, the development of digital culinary applications, and for technology-based diet and health purposes (Zidni & Akbar, 2024).

Image-based food classification is a branch of digital image processing that has a high level of complexity. This is due to the many visual factors that influence the appearance of food, such as color, texture, lighting, shooting angle, and variations in the shape and presentation of the food itself (Darma

Udayana & Nugraha, 2020). In the context of Padang food, the classification challenge increases because many types of side dishes have high visual similarities, such as gulai tunjang, gulai tambusu, gulai ikan, which all have a dominant brown and red color and are served in an unstructured form (Fadlia & Kosasih, 2020).

Several recent studies have also explored food classification using CNN with local datasets. For instance, (Zidni & Akbar, 2024) successfully classified traditional foods from Pasuruan using CNN with an accuracy of 72%, while (Citra et al., 2023) applied EfficientNetV2 for Indonesian food recognition and achieved better generalization compared to standard CNN. Similarly, (Mukti et al., 2023) emphasized the importance of dataset preprocessing and augmentation in improving classification results, which is consistent with the present study's findings. These works confirm that CNN-based models remain effective for food recognition tasks, particularly when supported by a balanced and sufficiently large dataset. Compared to these studies, our research focuses more specifically on Padang cuisine with nine food classes that have very high visual similarity, making the classification task more challenging yet contributing novel insights into local culinary recognition (Altim et al., 2023).

To address this gap, the present study develops a CNN-based model specifically designed to classify nine categories of Padang traditional foods. This contribution provides empirical evidence of CNN effectiveness in handling highly similar local food images and enriches the body of knowledge on deep learning applications in Indonesian culinary image recognition (Nugroho et al., 2020)(Wita & Liliana, 2022).

Based on this background, this study aims to build and test a Padang food image classification model using a CNN architecture. The developed model is expected to be able to recognize and differentiate several types of Padang food with high accuracy. This research contributes not only to the development of deep learning-based image classification technology but also to the preservation of local culinary culture through a scientific and data-driven approach.

MATERIALS AND METHODS

Research Stages

The research was conducted through several stages to ensure systematic implementation, as follows:

1. Problem Identification and Literature Review

At this stage, the main problem in recognizing Padang food images was identified. A literature review was carried out to examine previous studies on food image classification and CNN applications (Citra et al., 2023).

2. Data Collection and Preprocessing

Images of Padang traditional foods were collected from various sources. The dataset was then cleaned, resized, and augmented to increase data variability and support better training performance (Mukti et al., 2023).

3. Model Design and Development

A Convolutional Neural Network (CNN) architecture was designed and implemented. The model parameters, such as number of epochs, learning rate, and batch size, were set according to experimental needs (Ardiansyah & Itje Sela, 2023).

4. Model Training and Validation

The dataset was split into training and validation sets. The CNN model was trained for 20 epochs, and performance was monitored through accuracy and loss values (Triase & Samsudin, 2020).

5. Model Evaluation and Testing

Evaluation was conducted using metrics such as confusion matrix, training/validation accuracy, and loss values. In addition, testing was performed on new food images to measure the model's predictive ability (Sowmiya et al., 2024).

6. Result Analysis and Conclusion

The results were analyzed to assess the effectiveness of the CNN model in classifying Padang food images. Finally, conclusions and implications were drawn regarding the contribution of this research to food image recognition and future applications (Indraswari et al., 2021).

Data Collection Techniques

The following are data collection techniques used to support this research:

1. Observation was conducted by collecting image data of Padang traditional foods. There are nine food categories used as research objects, namely omelet, chili egg, cow tendon curry, stuffed intestine curry, fish curry, dendeng batokok, rendang, ayam pop, and fried chicken. The data were obtained from two sources: direct photographs taken using a smartphone camera and images collected from publicly available internet resources. This observation aimed to ensure that the dataset contained sufficient variations in terms of image angles, lighting conditions, and food presentation (Wulandari et al., 2020).
2. Literature Study At this stage, the author conducted a study on the research object by

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reviewing references from books, journals, and literature available on the internet (Juli & Timur, 2024). The literature study was carried out to obtain relevant theoretical foundations, strengthen the understanding of food image classification, and support the application of the Convolutional Neural Network (CNN) method in this study (Grandis et al., 2021).

Model Architecture

The model used in this study is a Convolutional Neural Network (CNN), which is designed with several convolutional, pooling, and fully connected layers (Nurkhasanah & Murinto, 2021). The model is built using the TensorFlow and Keras libraries in Python (Umam & Handoko, 2020).

The general structure of the model is as follows:

1. Input Layer: Image size 180x180 pixels RGB
2. Convolutional Layers: Multiple convolutional layers with 3x3 kernel and ReLU activation function
3. Pooling Layers: MaxPooling 2x2 to reduce dimensionality
4. Dropout Layers: To prevent overfitting (dropout rate 0.2 to 0.5)
5. Fully Connected (Dense) Layers: For final classification
6. Output Layer: Softmax to map to 9 classes.

Model Evaluation

The model was evaluated using the following approaches:

1. Accuracy and Loss Graph

The graph shows the model's learning trend from epoch to epoch. The graph shows a steady increase in accuracy and a decrease in loss, with the optimal point at epoch 15.

2. Confusion Matrix

A classification matrix was used to evaluate the model's ability to distinguish between classes. Some classes, such as ayam pop (pop chicken) and dendeng batokok (spicy beef jerky), had high accuracy, while gulai tunjang (spicy beef curry) showed numerous classification errors.

3. Error Analysis Per Class

The model was further evaluated through a classification error graph per class, which showed that visually similar classes were more prone to errors.

4. New Image Prediction

The model was tested on previously unrecognized images. The results showed that, although the confidence was still relatively low (- 25%), the model successfully predicted the correct label.

RESULTS AND DISCUSSION

Dataset Collection Results

The dataset used in this study consisted of a total of 1,350 images of Padang traditional foods covering nine categories: omelet (150), chili egg (150), cow tendon curry (150), stuffed intestine curry (150), fish curry (150), dendeng batokok (150), rendang (150), ayam pop (150), and fried chicken (150). Images were obtained from two sources: (1) direct photographs captured with a smartphone camera under varying lighting conditions and shooting angles, and (2) publicly available images collected from the internet to enrich data diversity. All images were resized to 180 × 180 pixels (RGB) and underwent preprocessing steps such as normalization and augmentation (rotation, flipping, and zooming) to increase variability and minimize overfitting. The dataset was split into 70% training, 20% validation, and 10% testing to ensure systematic model evaluation.

Research result

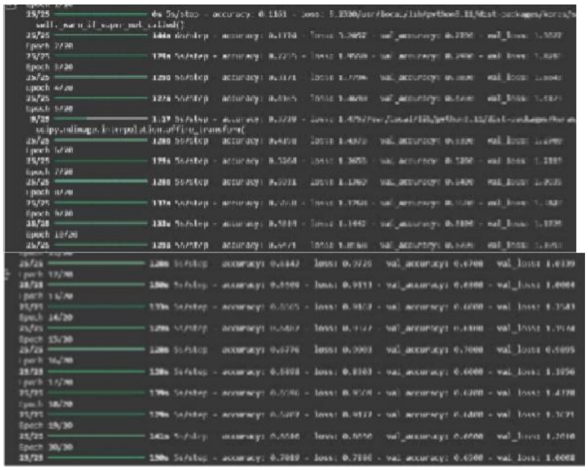
The CNN model was trained for 20 epochs. The following table summarizes the accuracy and loss at each epoch for training and validation:

Table 1. Training Results

Epoch	Accuracy (Train)	Loss (Train	Accuracy (Val)	Loss (Val)
1	0.1161	3.2320	0.2700	1.9827
2	0.2255	1.9550	0.2900	1.8216
3	0.3171	1.7794	0.3800	1.6843
4	0.4165	1.4690	0.4700	1.4123
5	0.3729	1.4757	0.5300	1.2700
6	0.4198	1.4373	0.5200	1.2119
7	0.5204	1.2653	0.6400	1.0935
8	0.5931	1.1369	0.5500	1.3143
9	0.5658	1.1268	0.6100	1.1726
10	0.5614	1.1442	0.6700	1.1093
11	0.6142	0.9729	0.6700	1.0339
12	0.6509	0.9153	0.6800	1.0004
13	0.6565	0.9162	0.6000	1.2543
14	0.6482	0.9327	0.6100	1.1974
15	0.6776	0.9003	0.7000	0.9895
16	0.6898	0.8303	0.6000	1.1956
17	0.6596	0.9569	0.6200	1.4328
18	0.6702	0.9122	0.6400	1.2621
19	0.6816	0.8650	0.6600	1.2010
20	0.7019	0.7886	0.6500	1.0008

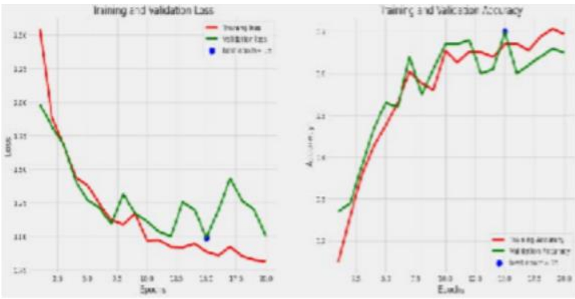
Source: (Research Result, 2025)

The Table 1 shows that training and validation accuracy significantly increased with each epoch, while the loss value continued to decrease. Epoch 15 produced the best performance, with a validation accuracy of 70% and a validation loss of 0.98.



Source: (Research Result, 2025)
Figure 1. Training Log Output for Each Epoch

Figure 1 displays the training log of a CNN model over 20 epochs. The log shows a gradual increase in model performance. In the first epoch, training accuracy was still very low at 11.6% with a loss of 3,232, while validation accuracy only reached 27.0% with a loss of 1,982. As training progressed, the model showed significant improvements in accuracy and a decrease in loss. Training accuracy steadily increased to 70.2% in the 20th epoch, while validation accuracy reached 65.0%. The training loss also continued to decrease to 0.788, and the validation loss reached its lowest point of 0.989 around the 15th epoch. These logs indicate that the model is learning progressively and is not experiencing severe overfitting, as indicated by the small difference between training and validation accuracy.



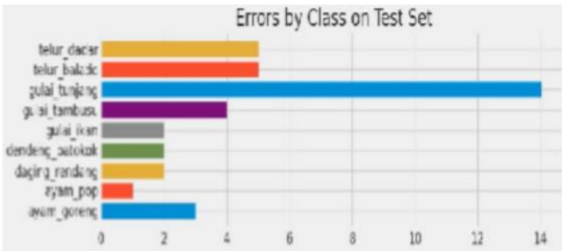
Source: (Research Result, 2025)
Figure 2. Training Validation Accuracy and Loss Graph

Figure 2 above illustrates a graphical visualization of model accuracy and loss versus the number of epochs during the training and validation processes. The left graph shows a consistent decrease in loss values for both training (red line) and validation (green line) data, with the blue dot at epoch 15 marking the best validation loss. Meanwhile, the right graph shows a fairly steady increase in accuracy across both data types. The red line representing training accuracy increases gradually until it approaches 70%, while the green line representing validation accuracy shows a similar trend with slight fluctuations after epoch 15. Both graphs demonstrate that the model has good learning capabilities and fairly strong generalization to new data.

Model Evaluation

Evaluation using a confusion matrix and error graphs per class shows that the model performs quite well for most classes. However, the class*goulash_tunjang*had the largest number of misclassifications, namely 13 times, followed by*omelette* and *spicy eggs*. On the other hand, classes like*jerky_batokok* and *chicken_pop*shows the most accurate prediction results.

Classification errors primarily occurred in classes with similar visual appearance or inconsistent image lighting. The model tended to confuse the gulai classes due to the similarity in texture and color of the sauce.



Source: (Research Result, 2025)
Figure 3. Bar Chart of Error per Class

Figure 3 shows a graph of the number of classification errors of the CNN model for each food class. From the graph, it can be observed that the class *goulash* occupies the highest position in the number of errors, namely 13 times. This shows that the model has difficulty in disting uishing *goulash* from other classes, possibly due to the visual similarity to other soup-based foods such as *tambusu curry* or even *fried chicken*. In addition, the class *spicy eggs* and *omelette* also has a fairly high error rate, which can be explained by the similarity in color and presentation of the two foods. In contrast, classes such as*pop chicken* and *batokok jerky*has a relatively low number of errors, indicating that the model is able to recognize the visual characteristics of the food more consistently and accurately. This graph is an important indicator of model weaknesses in certain classes and provides guidance for collecting additional data or improving preprocessing to improve classification performance.

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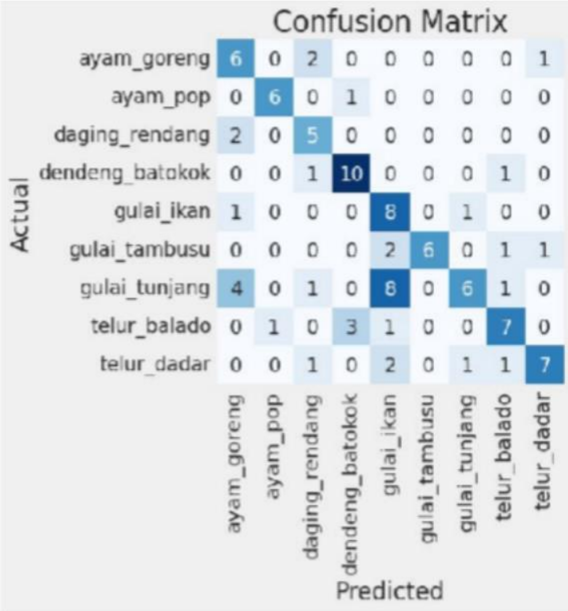


Source: (Research Result, 2025)
Figure 4. Confusion Matrix between Classes

Figure 4 shows a confusion matrix depicting the model's performance in classifying nine food classes. The confusion matrix displays the relationship between the original labels and the model's predicted labels, where values on the main diagonal represent the number of correct predictions, and values outside the diagonal indicate misclassifications. This matrix demonstrates the model's ability to classify *pop chicken* And *batokok jerky* with a high level of accuracy, indicated by the dominant number of correct predictions in the corresponding rows and columns.

However, predictions against goulash shows many errors, where images from this class are often classified as *fried chicken* or *omelette*. Some errors also occur between classes of curry, such as tambusu curry which is predicted as *fish curry.*

These results are consistent with findings from other CNN-based food classification studies, where visually similar dishes often lead to higher error rates (e.g., various noodle dishes or curry-based foods). Previous works (Iskandar & Kristianto, 2023) also reported that food categories with overlapping textures and colors are the most difficult to distinguish. This suggests that the limitations observed in this study are not unique to Padang cuisine but represent a common challenge in food image classification.

Therefore, future improvements could involve increasing the dataset size, especially for classes with high error rates, applying more advanced augmentation techniques to enhance visual variability, or using transfer learning with deeper CNN architectures such as ResNet or EfficientNet. Such strategies are expected to reduce misclassification rates and improve overall model robustness.

These results are in line with recent works that addressed food image classification challenges in datasets with visually similar classes. For instance, (Zidni & Akbar, 2024) reported that CNN often misclassified dishes with similar textures and colors in Pasuruan traditional foods, showing a pattern similar to the errors observed in gulai classes in this study. Likewise, (Sowmiya et al., 2024) emphasized that uncertainty in predictions tends to increase when classes share overlapping visual features, even when deep learning models are applied. This consistency across studies suggests that the misclassification problem is a common issue in local food image recognition and highlights the importance of enlarging datasets and exploring advanced architectures such as ResNet or EfficientNet for improved robustness.

Model Prediction Example

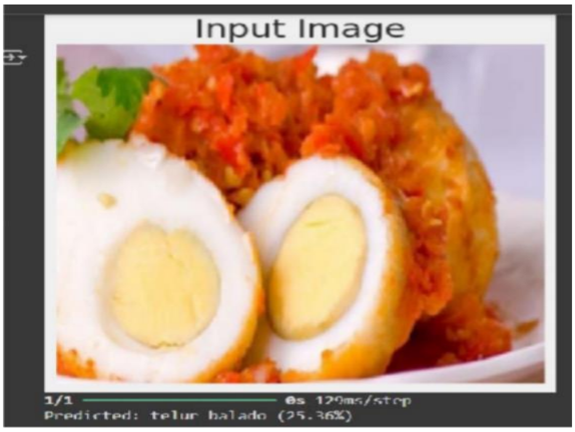
The example of model prediction on a new image shows that the CNN correctly classified the food category, but with a confidence value of only 25%. This outcome indicates that while the model's decision coincided with the correct class, the probability distribution across classes was relatively flat, suggesting high uncertainty. Several factors may contribute to this condition: visual similarity between the predicted class and other classes in the dataset (e.g., dishes with similar textures or colors), limited training samples for that class, which reduces the model's ability to form strong feature representations, and potential inconsistencies in image quality, lighting, or angle that make the features less distinctive.

From a practical perspective, a correct prediction with low confidence raises important implications. In real-world applications, such as digital food catalogs or automated restaurant ordering systems, predictions with confidence below a certain threshold (e.g., 50%) should not be considered reliable without additional validation. Instead, the system could be designed to present the top-3 prediction classes to the user, enabling human confirmation when the model is uncertain. Furthermore, enhancing dataset size and diversity, particularly for classes with overlapping visual features, and applying advanced augmentation strategies could improve the model's confidence in future iterations.

This analysis emphasizes that although the model can technically "guess" the right class, low-confidence predictions should be treated cautiously in deployment scenarios to maintain user trust and system reliability.

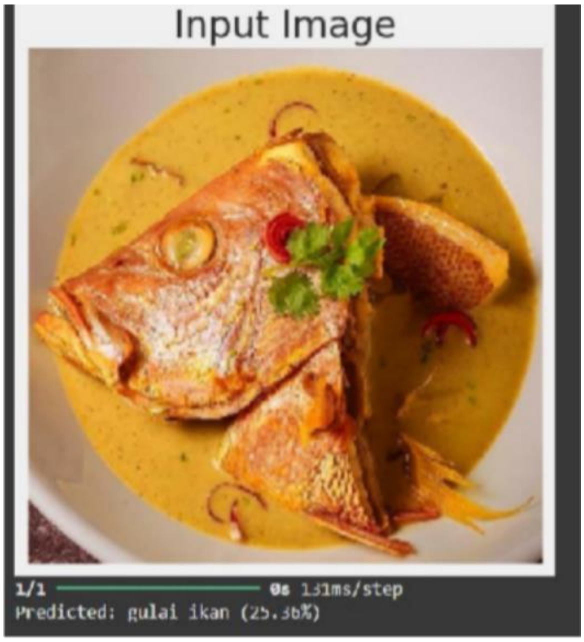
Source: (Research Result, 2025)
Figure 5. Prediction of Batokok Dendeng (25.36%)

Figure 5 shows an example of a food image.*batokok jerky*. The model successfully predicted this image with the correct label, namely *jerky_batokok*, and achieved a confidence level of 25.36%. Although the confidence level is still relatively low, these prediction results indicate that the model has recognized the distinctive visual patterns and characteristics of jerky, such as the dark color, dry texture, and shape of the meat pieces.



Source: (Research Result, 2025)
Figure 6. Prediction of Balado Eggs (25.36%)

Figure 6 is an image *spicy eggs*, a typical Minang dish made with boiled eggs coated in red chili sauce. The model again provided accurate predictions with the label *spicy eggs* and a confidence level of 25.36%. This success indicates that the model is quite sensitive to striking color features, such as the bright red of the chili sauce, which distinguishes balado eggs from other egg-based dishes



Source: (Research Result, 2025)
Figure 7. Fish Curry Prediction (25.36%)

Figure 7 shows the image *fish curry*, one of the yellow-spiced dishes with a thick sauce typical of Padang. The model predicts this image as *fish curry* with a confidence level of 25.36%. These results indicate that the model is capable of recognizing soups with distinctive colors like yellow-orange and shapes resembling fish pieces, although difficulties may arise in images with less than ideal shooting angles or lighting.

Although the model's confidence level is still low, the predictions for these three images are all accurate. This indicates that the model has successfully developed a fundamental understanding of each food class. To further improve confidence and accuracy, it is recommended that the model be trained on a larger and more varied dataset, along with more optimal image preprocessing.

CONCLUSION

Based on the results of the research that has been conducted, it can be concluded that the Convolutional Neural Network (CNN) model was successfully used to automatically classify Padang food images. The model was trained for 20 epochs and showed an increase in training accuracy of up to 70.2% and validation accuracy of 65%, with a continuously decreasing loss value. Evaluation using a confusion matrix and classification error graphs showed that several classes such as ayam pop and dendeng batokok had high accuracy, while the gulai tunjang and telur balado classes tended to experience misclassification due to visual similarities between the foods. The model was also tested using new images not included in the training data, and the results showed that the model was able to provide accurate predictions even though the confidence score was still relatively low (~25%). This proves that the model has quite good generalization capabilities. Thus, this CNN model is worthy of further development as the basis for an image-based food recognition system that can be used in culinary applications, food ordering systems, and automatic food catalogs. Compared to previous studies on Indonesian food recognition, this research makes a novel contribution by focusing specifically on Padang cuisine with nine food categories that exhibit high visual similarity. This unique context makes the classification task more complex but also provides valuable insights into the application of CNN for local culinary recognition.

REFERENCE

Altim, M. Z., Basalamah, A., Kasman,Syamsul, R. A., & Yudhistira, A.. (2023). Implementasi Convolutional Neural Network (Cnn) Untuk Penentuan Kualitas Beras Berdasarkan Bentuk Dan Warna. *Jurnal INSTEK (Informatika Sains Dan Teknologi)*, *8*(2), 380–386. https://doi.org/10.24252/instek.v8i2.42968

Ardiansyah, R., & Itje Sela, E. (2023). Implementasi Convolutional Neural Network Untuk Klasifikasi Jenis Beras Berdasarkan Citra Digital. *Indonesian Journal of Computer Science*, *12*(6), 4657–4663. https://doi.org/10.33022/ijcs.v12i6.3520

Citra, E. E., Fudholi, D. H., & Dewa, C. K. (2023). Implementasi Arsitektur EfficientNetV2 Untuk Klasifikasi Gambar Makanan Tradisional Indonesia. *Jurnal Media Informatika Budidarma*, *7*(2), 766. https://doi.org/10.30865/mib.v7i2.5881

Darma Udayana, I. P. A. E., & 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

Fadlia, N., & Kosasih, R. (2020). Klasifikasi Jenis Kendaraan Menggunakan Metode Convolutional Neural Network (Cnn). *Jurnal Ilmiah Teknologi Dan Rekayasa*, *24*(3), 207–215. https://doi.org/10.35760/tr.2019.v24i3.2397

Grandis, G. F., Arumsari, Y., & Indriati. (2021). Seleksi Fitur Gain Ratio pada Analisis Sentimen Kebijakan Pemerintah Mengenai Pembelajaran Jarak Jauh dengan K-Nearest Neighbor. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *5*(8), 3507–3514.

Indraswari, R., Rokhana, R., & Herulambang, W. (2021). Melanoma image classification based on MobileNetV2 network. *Procedia Computer Science*, *197*, 198–207. https://doi.org/10.1016/j.procs.2021.12.132

Iskandar, J. S., & Kristianto, R. P. (2023). Pengenalan dan Klasifikasi Ragam Kue Indonesia menggunakan Arsitektur ResNet50V2 pada Convolutional Neural Network (CNN). *Prosiding Seminar Nasional AMIKOM Surakarta*, *1*(November), 81–92. https://ojs.amikomsolo.ac.id/index.php/semnasa/article/view/53

Juli, V. N., & Timur, N. T. (2024). *Klasifikasi Citra Digital Bumbu dan Rempah Dengan Algoritma Convolutional Neural Network (CNN)*. *2*(3).

Linarti, U., Soleliza Jones, A. H., Zahrotun, L., & Rahmawati, A. (2024). Penerapan Metode K-Medoids Guna Pengelompokan Data Usaha Mikro, Kecil dan Menengah (UMKM) Bidang Kuliner Di Kota Yogyakarta. *Jurnal Ilmu Komputer Dan Sistem Informasi (JIKOMSI)*, *7*(1), 37–45. https://doi.org/10.55338/jikomsi.v7i1.2194

Mukti, A., Hadiyanti, A. D., Nurlaela, A., & Panjaitan, J. (2023). Sistem Analisa Sentiment Bakal Calon Presiden 2024 Menggunakan Metode NLP Berbasis Web. *Soscied*, *6*(1), p-ISSN.

Nugroho, P. A., Fenriana, I., & Arijanto, R. (2020). Implementasi Deep Learning Menggunakan Convolutional Neural Network (CNN) Pada Ekspresi Manusia. *Algor*, *2*(1), 12–21.

Nurkhasanah, & Murinto. (2021). Klasifikasi Penyakit Kulit Wajah Menggunakan Metode Convolutional Neural Network Classification of Facial Skin Diseases Using the Method of the Convolutional Neural Network. *Sainteks*, *18*(2), 183–190. https://www.kaggle.com/datasets

Sowmiya, S., Umapathy, S., Alhajlah, O., Almutairi, F., Aslam, S., & Ahalya, R. K. (2024). F-Net: Follicles Net an efficient tool for the diagnosis of polycystic ovarian syndrome using deep learning techniques. *PLoS ONE*, *19*(8 AUGUST), 1–22. https://doi.org/10.1371/journal.pone.0307571

Triase, T., & Samsudin, S. (2020). Implementasi Data Mining dalam Mengklasifikasikan UKT (Uang Kuliah Tunggal) pada UIN Sumatera Utara Medan. *Jurnal Teknologi Informasi*, *4*(2), 370–376. https://doi.org/10.36294/jurti.v4i2.1711

Umam, C., & Handoko, L. B. (2020). Convolutional Neural Network (CNN) Untuk Identifkasi

Karakter Hiragana. *Prosiding Seminar Nasional Lppm Ump*, *0*(0), 527–533. https://semnaslppm.ump.ac.id/index.php/semnaslppm/article/view/199

Wita, D. S., & Liliana, D. Y. (2022). Klasifikasi Identitas Dengan Citra Telapak Tangan Menggunakan Convolutional Neural Network (CNN). *Jurnal Rekayasa Teknologi Informasi (JURTI)*, *6*(1), 1. https://doi.org/10.30872/jurti.v6i1.7100

Wulandari, I., Yasin, H., & Widiharih, T. (2020). Klasifikasi Citra Digital Bumbu dan Rempah Dengan Algoritma Convolutional Neural Network (CNN). *JURNAL GAUSSIAN*, *9*(3), 273–282. https://doi.org/10.62951/repeater.v2i3.81

Zidni, E., & Akbar, M. (2024). Klasifikasi Citra Makanan Khas Kota Pasuruan menggunakan Convolutional Neural Network. *Informatics and Artificial Intelligence Journal*, *1*(2), 65–72. http://jurnal.forai.or.id/index.php/forai/article/view/10